# FINANCIAL MARKETS, POLITICAL VARIABLES AND EXTREME EVENTS

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# Abstract

This thesis investigates the dynamics of financial markets from different perspectives. First, we analyze the impact of different political variables on market prices. We show that the quality of economic policy and the institutional effectiveness display surprisingly low correlation and play a crucial role for the stock, CDS and forex markets. Second, focusing on extreme events, we show that the extreme correlation between asset returns and trading volumes is very low during stock market booms and crashes. Third, in order to optimally deal with these extreme events, we study the predictive accuracy of an entropy-based estimator to forecast asset prices. We compare this entropic estimator with a standard quadratic technique based on the mean square error, and we show that the entropy attains higher forecasting precision. Finally, we study pairs trading, a well-known investment strategy that is applied to the Italian stock market, and investigate the determinants of its profitability.

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# Introduction

In this thesis, I investigate the dynamics and the behavior of financial markets from several perspectives. The recent financial crisis has underscored the importance of studying the dynamics of the markets not only in normal times, but also and especially when extreme events occur. The main goal of this thesis is to shed light on and understand how the markets behave, both in normal and extreme conditions.

In Chapter 1 we start by discussing the crucial importance that political variables have for explaining the dynamics of the markets. Starting from my passion for politics and my intellectual curiosity to shed more light on the relationship between politics and finance, I investigate and discover how relevant some political variables turn out to be for the impact that they have on the markets. I felt the interest as well as the need to investigate these issues given the relatively limited amount of published academic papers that study the area at the intersection of politics, political economics and finance. Many gaps have still to be filled in the literature, and I was motivated to start filling some of these gaps for a better and deeper understanding of the channels through which politics shapes not only the society and the economic environment in which we live, but also financial markets.

Chapter 1 therefore discusses the importance of two different political variables: economic policy and institutional effectiveness. This research is motivated by an empirical observation in the data at my disposal: economic policy and institutional effectiveness display low correlation. After careful investigation, I discovered that political scientists argued that, also theoretically, policy and politics represent two different forces, which need to be disentangled and studied in their differential impact and reciprocal interplay.

Moreover, chapter 1 shows that disentangling further institutional effectiveness into its main components can be beneficial. I provide evidence that some purely institutional variables as political instability, corruption, and legal and administrative restrictions, also display low correlation with each other and, most importantly, with economic policy as well. Focusing on both developed countries and emerging markets, Chapter1 shows that better policymaking, higher political stability, and lower levels of corruption and restrictions lead to i) better stock market performance, ii) lower CDS spreads and iii) lower depreciation rates of the national currency with respect to the US dollar.

Crucially, Chapter 1 shows that combining policy and stability can be highly beneficial, exploiting their low correlation. Countries characterized, simultaneously, by effective policymaking in a politically stable environment experience even higher stock market performance, lower CDS spreads and lower currency depreciation, with respect to the univariate cases of considering either policy alone or stability by itself. These findings are relevant for the policymaker, the society as a whole and for investors who aim to replicate the trading strategies described in Chapter 1 and which are able to consistently generate significant abnormal returns. The work described in this chapter led to the need for a theoretical model, which has been developed during my PhD and will be published after the thesis. This paper will be co-authored by myself, Professor Poncet and Professor Zenios, with whom I have been working to incorporate and describe in a theoretical model the effects of these political variables on the markets.

Political events can bring about shocks to the real economy as well as to the financial markets. Many recent political issues represent a dangerous threat nowadays that either already impacted the markets or that are likely to affect them in the near future. To cite only a few of them, I can recall the recent Brexit, the raise of populisms across Europe, the dangerous behavior of the North-Korean dictator, the sovereign debt crisis and the future of the European Union. When these shocks impact the market, we need to understand the behavior and reaction of the latter. Stock market crashes have been studied in the past, but they become even more important nowadays in a political environment rich of uncertainty and with the markets that are highly sensitive to negative or worrisome political news.

Hence, Chapter 2 investigates the behavior of market participants during stock market crashes as well as stock market booms. Making use of the statistical tools provided by extreme value theory, I show that also the extreme correlation between returns and trading volume during extreme events is very low. The interpretation is the following: high trading volume is not necessarily associated with high returns in absolute value. Hence, more trading activity cannot be seen as the main cause of stock market crashes. The results reported in Chapter 2 are consistent with a trade-misinterpretation hypothesis put forward by Gennotte and Leland (1990). Asymmetric information between market participants, algorithmic trading and positive-feedback strategies play a relevant role in driving the markets to extreme price movements.

After having studied the impact of extreme events on the stock market, the next logical step followed by this thesis is to propose some tools to optimally deal with the presence of market crashes and booms. It is well-known that the existence of extreme events is one of the main causes of the leptokurtosis of stock returns. One of the most important issues that has been and is still debated in the academic literature is how to forecast stock returns. The presence of jumps in the stochastic process underlying the time-series of asset returns renders the predictability of future returns an even more complex task.

More specifically, the presence of extreme events leading the asset return distribution to be leptokurtic creates serious issues when the forecasting algorithm is based on a quadratic criterion, as in most applications in the extant literature. When forecasting, one needs to minimize a cost function, and the most common choice is the mean square error (MSE). Forecasting through the minimization of a quadratic cost function, however, turns out to be a flawed methodology when the impact of the higher moments of the underlying stochastic process is not negligible. Needless to say, quadratic criteria for leptokurtic distributions with a strong impact of extreme events cannot be an optimal choice.

To solve these issues, Chapter 3 proposes and tests a forecasting algorithm that minimizes the entropy of the error distribution instead of the sum of their squares. The entropy is particularly suitable to deal with non-Gaussian returns in that it takes into account the whole probability distribution, empirically estimated from the data, instead of relying on the first two moments only as does the MSE. The entropy can thus capture the impact of these extreme events. Chapter 3 justifies in detail the choice of the entropy and describes a numerical method through which the estimator that minimizes the entropy of the forecasting error distribution can be derived. This estimator is tested on simulated time-series, starting from a perfectly linear and Gaussian environment, and progressively departing from the Normality assumptions, by including CGMY (Carr, Madan, Geman, Yor, 2003) errors and non-linearities in the data generating process.

Chapter 3 shows that an entropic cost function can be beneficial with respect to a quadratic criterion in terms of higher predictive accuracy. A relation of stochastic dominance of the entropic algorithm over the quadratic one can be established. When the stochastic process is Gaussian and linear, the entropic algorithm attains the same forecasting precision as the quadratic one. Moreover, the difference in the forecasting precision between the entropic and the MSE-based techniques is directly proportional to the degree of non-normality and non-linearities present in the data generating process. This sheds light on the relevance to make use of an entropic cost function when forecasting leptokurtic distributions, as, for instance, asset returns, which are strongly impacted by extreme events.

To conclude the thesis, Chapter 4 discusses pairs trading, an investment strategy that is applied to the Italian stock market. Given that some stocks tend to co-move on the market, forecasting the future dynamics of one security with respect to another is possible. Chapter 4 shows the profitability of such a strategy and analyzes if liquidity can be a driver of these statistical arbitrage returns. To achieve this goal, I run a natural experiment on the Italian stock market, which experienced a unique change in market strucutre in 2001. This allows me to investigate whether market structure and liquidity matter to explain these strategy returns. I show that expected returns are indeed a positive function of the expected illiquidity. Pairs trading returns incorporate, ex ante, a required compensation for this expected illiquidity.

# Résumé de Thèse

Cette thèse de doctorat étudie les dynamiques des marchés financiers quand des événements extrêmes et des variables politiques sont pris en compte. Il est reconnu que les crises financières aussi bien que les événements politiques nationaux et internationaux ont un impact significatif sur les bourses mondiales, et cet impact est devenu encore plus important avec l'intégration accrue des marchés financiers, de telle sorte par exemple qu'un choc dans un pays peut avoir rapidement des répercussions sur les autres marchés.

Le premier chapitre de cette thèse se différencie de la littérature traditionnelle qui étudie les risques politiques en introduisant dans le domaine de la finance une théorie qui a valu à son auteur, Douglass C. North, le prix Nobel d'économie en 1993, notamment pour son travail sur les institutions et le changement institutionnel et leur impact sur la performance économique des pays. Cette théorie est bien reconnue dans le domaine des sciences politiques, mais elle n'a jamais été appliquée en finance pour étudier les liens entre les événements politiques et la performance des marchés financiers.

Introduire la théorie de Douglass C. North est essentiel pour pouvoir distinguer l'impact de la politique économique d'un gouvernement de celui dû à la stabilité politique de ce gouvernement même et des institutions du pays. Le premier chapitre de cette thèse décrit les raisons pour lesquelles il faut séparer ces deux composants du risque politique, qui sont empiriquement faiblement corrélés. Les pays qui ont un gouvernement et des institutions stables ne sont pas forcément ceux qui adoptent et mettent en œuvre les politiques économiques les plus efficaces pour leur pays. Symétriquement, certains pays dans leur histoire ont vécu des phases d'instabilité politique pendant lesquelles, néanmoins, ils ont réussi à imposer des politiques économiques qui ont eu un impact positif sur la croissance.

Ces deux variables, la stabilité politique et la politique économique, sont donc différentes et ont un impact différentiel sur les marchés financiers. Cela est dû au fait qu'elles sont différentes au niveau théorique, comme magistralement expliqué par Douglass C. North, et ont une corrélation faible dans les données, comme démontré au chapitre 1 de cette thèse. Par conséquent, se concentrer sur une variable seulement fait perdre aux modèles un pouvoir explicatif qui est quantifié dans ce chapitre.

Afin d'appliquer la théorie de North, il faut résoudre le problème de mesure des variables politiques, ce qui est difficile car il n'y a pas dans la littérature de bases de données qui couvrent tous les pays développés et émergents sur une période longue et avec une granularité satisfaisante. Le premier chapitre décrit une base de données, diffusée par le centre de recherche allemand IFO, qui fournit des ratings (notations) sur la confiance que les experts ont à propos de la politique économique d'un pays et de la stabilité du gouvernement. Les données ont une fréquence semi-annuelle et couvrent les pays développés aussi bien que les émergents sur la période 1992-2016. L'utilisation de cette base de données est nouvelle dans la littérature en finance et garantit de pouvoir proprement séparer la politique économique de la stabilité politique.

Le premier chapitre de la thèse montre également que les deux variables ont un impact différentiel et important sur les marchés financiers de chaque pays. De plus, la politique économique et la stabilité politique peuvent prédire les futurs taux de croissance du PIB de chaque pays, et cela montre qu'ils ont un pouvoir prédictif dans le long terme. De manière importante, le chapitre 1 montre aussi que les principaux modèles d'évaluation d'actifs qui ont été proposés dans la littérature ne peuvent pas expliquer les rendements élevés qui peuvent être générés par des stratégies de gestion de portefeuille basées sur les informations fournies par ces variables politiques.

Le premier chapitre montre donc comment i) incorporer et appliquer en finance une théorie connue dans le domaine des sciences politiques qui a valu à son concepteur le prix Nobel d'économie, ii) utiliser de nouvelles mesures de confiance des experts dans la politique économique d'un pays et de sa stabilité politique, iii) créer des stratégies de trading qui génèrent des alphas (profits anormaux) remarquablement élevés, et iv) prédire les futurs taux de croissance du PIB à l'aide de ces variables politiques, qui jouent un rôle décisif sur les marchés financiers.

Si le chapitre 1 se focalise sur les variables politiques, le chapitre 2 étudie l'impact de tous les types d'événements extrêmes sur le marché des actions. En particulier, on analyse la corrélation extrême entre les rendements boursiers et les volumes échangés sur l'indice boursier américain SP500 depuis la deuxième guerre mondiale jusqu'à 2016. On trouve que la corrélation entre les changements extrêmes des prix des actifs boursiers et les volumes échangés est très faible, contrairement à ce que l'on pourrait penser. Cela est observé durant les crises financières aussi bien que pendant les booms boursiers.

La leçon à tirer du chapitre 2 est que des rendements extrêmement élevés en valeur absolue ne sont pas corrélés avec des volumes échangés extrêmes. On n'observe pas les volumes les plus élevés avec les booms et les crashs boursiers. Cela renforce les arguments de Gennotte et Leland (1990) selon lesquels l'asymétrie d'information parmi les participants au marché peut jouer un rôle essentiel pour déclencher un crash boursier même sans des volumes échangés anormalement élevés. Les stratégies dites à effet de feedback positif et le trading algorithmique sont aussi des explications importantes dans la théorie de Gennotte et Leland (1990). De plus, la méthodologie appliquée et présentée au chapitre 2 montre comment calculer les rendements boursiers limites au-delà desquels on peut parler de rendements vraiment extrêmes.

Crises politiques et événements politiques soudains peuvent être la cause de la chute des prix et des événements extrêmes qui affectent les bourses globales. Après avoir décrit l'impact de ces variables politiques et des événements extrêmes en général dans le chapitre 2, cette thèse étudie un algorithme statistique nouveau pour effectuer la prévision des prix des actifs financiers en présence des événements extrêmes. L'idée à la base de ce chapitre est que les rendements des titres boursiers ne suivent pas une distribution gaussienne, et que donc la prévision de leurs prix futurs n'est pas optimale tant qu'elle est faite à partir de la minimisation de l'erreur quadratique moyenne qui constitue la méthode standard. Pour améliorer la prévision en présence d'événements extrêmes et, en général, de distributions non-normales, le chapitre 3 propose un algorithme de prévision nouveau qui minimise l'entropie de la distribution plutôt que son deuxième moment.

Le choix de l'entropie est motivé par le fait que cette dernière prend en considération toute l'information présente dans la distribution des rendements boursiers qui est observable quand on en fait la prévision. Il est donc logique de maximiser l'information présente dans toute la série de données au lieu de se focaliser exclusivement sur le deuxième moment, surtout quand la distribution des rendements est fortement asymétrique et caractérisée par des queues épaisses. Le chapitre 3 montre comment implémenter un algorithme numérique qui permet de minimiser l'entropie et le compare à l'algorithme standard dans la littérature qui minimise l'erreur quadratique moyenne.

Pour valider que le choix de l'entropie produit des gains dans la précision de l'estimation, dans le chapitre 3 on décrit également des expériences faites sur des séries simulées avec certaines caractéristiques qui ressemblent à celles des rendements des actifs financiers. Nous montrons que l'entropie a une performance significativement meilleure que celle du critère basé sur l'erreur quadratique moyenne lorsqu'il faut prédire des processus stochastiques avec une erreur qui n'est pas gaussienne mais qui présente une distribution fortement asymétrique et comprenant des événements extrêmes.

Les résultats confortent la thèse selon laquelle un algorithme qui prend en compte l'impact d'événements extrêmes et des moments de la distribution supérieurs au deuxième peut avoir une performance meilleure par rapport à un algorithme traditionnel basé sur la minimisation de l'erreur quadratique moyenne. De plus, les expériences mises en œuvre montrent que la différence entre la performance de l'entropie vis-à-vis celle de l'erreur quadratique moyenne est proportionnelle au degré de non-linéarité et de non-normalité présente dans les données. L'algorithme fondé sur l'entropie peut donc s'avérer spécialement utile avec des séries qui ont été générées par un processus stochastique fortement non-normal, comme c'est le cas pour de nombreuses séries de rentabilité d'actifs financiers.

Cette thèse se termine par le chapitre 4 qui discute du problème de la liquidité sur le marché des actions et de son impact sur une stratégie d'investissement fameuse dénommée "pairs trading". Ce chapitre se concentre sur l'explication des rendements élevés générés par cette stratégie, et essaie de comprendre si la liquidité affecte les rendements de la stratégie. Pour atteindre cet objectif, on analyse le marché boursier italien en

2001, date à laquelle fut adoptée une réforme du marché des actions qui représente un contexte optimal pour étudier l'impact de la liquidité sur le marché. Cette réforme avait comme but d'augmenter la transparence et la gouvernance de certains titres, qui ont été inclus dans un indice nommé STAR. En particulier, un intermédiaire boursier spécialiste est assigné à chaque titre présent dans cet indice, afin d'améliorer la liquidité du titre. Après l'introduction de ce changement dans la réglementation, les titres inclus dans l'indice devraient avoir bénéficié d'une augmentation de liquidité.

Par conséquent, le chapitre 4 met en œuvre une expérience pour étudier si les investisseurs exigent d'être compensés par une prime de risque de liquidité qui est significativement différente avant et après l'introduction de cette nouvelle réglementation. Le premier pas concerne l'implémentation de cette stratégie de trading sur le marché italien dans la période qui précède et suit immédiatement l'introduction de la nouvelle réglementation. On montre que le "pairs trading" génère des rendements qui sont statistiquement significatifs et économiquement élevés et que les rendements attendus incorporent une prime de risque de liquidité.

L'analyse confirme aussi l'hypothèse selon laquelle, après l'introduction de la réglementation, la prime de risque de liquidité demandée par les investisseurs est mineure par rapport à la prime de risque exigée avant la nouvelle réglementation. Par conséquent, la liquidité est un facteur important qui affecte cette stratégie de trading. Les résultats suggèrent que la réduction du risque de liquidité perçu par les investisseurs grâce à la présence des spécialistes sur certains titres a eu l'effet prévisible de réduire les rendements moyens de la stratégie en réduisant la prime de risque de liquidité demandée par les investisseurs.

Globalement, cette thèse marque une étape importante pour une meilleure compréhension du fonctionnement des marchés financiers. Les études sur les événements extrêmes ont montré que, contrairement à ce que l'intuition suggère, ce ne sont pas les volumes échangés extraordinaires qui déclenchent les krachs et les booms boursiers. Nous avons aussi montré comment améliorer la prévision des futurs rendements quand ces derniers ne peuvent pas être décrits par une distribution normale. En outre, nous appliquons au domaine de la finance une théorie Nobélisée bien connue en science politique et qui nous guide pour étudier avec une précision méthodologique et conceptuelle l'impact de la politique économique et celui de la stabilité politique sur les marchés financiers. Ces variables, spécialement les facteurs politiques et les événements extrêmes comme les krachs boursiers, sont cruciales pour la société d'aujourd'hui, et le but ultime de cette thèse a été de fournir des outils et des analyses qui puissent aider à la compréhension de ces mécanismes qui revêtent une telle importance non seulement pour la communauté académique mais pour toute la société.

# Chapter 1

# Policy vs institutions: the differential impact of political variables on financial markets *

## Abstract

We propose a framework to describe and analyze the impact of political uncertainty on financial markets. We disentangle two conceptually related yet different channels through which politics affects the economic environment: the stability of the government and the functioning of the political institutions on the one hand, and the effectiveness of the economic reforms implemented by the government on the other. We therefore identify two different political variables affecting the markets: economic policy and political instability. We provide evidence of the low correlation that these variables display during the period 1992-2017 for a sample comprising 22 developed countries and 20 emerging markets. We show that these two variables have markedly different impacts on financial markets, in particular the stock, forex and CDS markets. We build trading strategies based on these two political indicators that are able to generate statistically and economically significant abnormal returns. Our findings shed light on the relevance

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of disentangling different political variables in order to better explain the dynamics of financial markets.

## 1.1 Introduction

Political events always played a crucial role in shaping the economic environment as well as the discussions in our society. However, especially nowadays, political issues are becoming increasingly relevant for our society and, needless to say, for financial markets. We can undoubtedly claim that, since the end of World War II, there has never been a period of such high political uncertainty across the globe, with the existence of many threats for our society. We currently face a number of political issues that are likely to impact our society, our economy and international financial markets.

To cite only a few of these political issues, we can recall the recent Brexit, the debates concerning the recent elections in the United States, the threat stemming from the dangerous behavior of the North-Korean dictator, the war in Syria and the dramatic geopolitical situation in part of Middle-East due to the presence of ISIS, the debt crisis and the discussions about the future of the European Union, the raise and spread of populisms across Europe, the cooling relationships between US and Russia, the fight for independence of Catalonia from Spain, and the strong increase in consensus obtained by extreme political parties as, for instance, the one of Marine Le Pen in France.

Overall, a growing distrust in politics and institutions is generally and certainly prevailing, at the very least across Europe, after the start of the financial crisis in 2008. This poses the question to evaluate how the effectiveness of these institutions is perceived not only by the society but also by the markets. Political stability is a crucial example of an institutional factor that has a clear impact on financial markets, and now more than ever it becomes key to understand how the stability of institutions affects the markets. On the other hand, this growing distrust also refers to governments and the economic policies that they implemented since the beginning of the crisis. In several countries, the ability of the governments to implement good policies able to restore significant long-run economic growth has been and is still highly questioned. This perception of distrust towards institutions and policies has a potentially strong impact on the markets. For these reasons, in this paper we investigate the differential impact of institutional effectiveness and economic policy on the markets.

Moreover, we also go deeper and we further disentangle the institutional effectiveness variable into its main components: political stability, corruption, and legal and administrative restrictions. The following example will clarify why this additional decomposition is important. Let us consider China and Italy. If we only looked at political stability, China would appear much more stable than Italy, since it is a quasi-democratic regime only with the Communist Party being at the government since many years. On the other hand, Italy changed five governments in the last six years, displaying high political instability. Nevertheless, if we analyze the institutional effectiveness from the perspective of rule of law and legal restrictions, China is definitely characterized by a higher probability that a cabinet gets closed without a proper democratic process. Therefore, separating the components of institutional effectiveness is a relevant issue in order to fully understand the differential impact of disentangled political variables on the markets.

Hence, we run our analysis on four main variables. The first layer is the distinction between *economic policy*, which describes all the aspects relative to the quality of the fiscal policies implemented by the government, and *institutional effectiveness*. The second layer consists of the further separation of the *institutional effectiveness* into its three main components: political stability, legal and administrative restrictions, and corruption. We analyze their differential impact on the stock, CDS and forex markets.

The remainder of this chapter is structured as follows. Section 1.2 will discuss some facts that highlight the main point of this paper, which is the low correlation between economic policy and political instability. We will describe some political events worldwide where economic policy and political instability moved in opposite directions, leading to completely different conclusions about the better or worse performance of a country, shedding light on how crucial it is to disentangle these two variables. In addition, we will present quantitative empirical evidence on the correlation over time and across countries between these two variables, which corroborates our theory. Section 1.3 reviews the extant literature on the links between politics and financial markets. We will mainly discuss two points: *i)* the literature that studied the relationship between economic policy, economic growth and financial markets, and *i)* the papers that focused on the link between institutions, economic growth and market performance. We contribute in this literature by showing the low correlation between policy and institutions, how to explain its impact on the markets and how an investor can exploit it. Section 1.4 presents the data, and Section 1.5 discusses the empirical results of our analyses, referred to the stock market, the CDS market and the forex market. Section 1.6 identifies the channels through which economic policy and political instability affect the financial markets, highlighting the cash-flow story on which this paper is based: in a politically stable environment characterized by high-quality policymaking, firms manage to produce more cash-flows and the economy grows at a higher pace. In Section 1.6 we show that our policy and stability variables forecast the short-term and long-run growth rates of GDP, industrial production and aggregate dividends. Section 1.7 concludes.

## 1.2 The low correlation between policy and politics

The most important consequence of the low correlation between policy and politics is that they might move in the same direction but also in opposite directions. *A priori*, there is no association between an increase in the quality of policymaking and an increase in institutional effectiveness. Better economic policies can be associated either with higher or lower institutional effectiveness. Hence, considering only a general political uncertainty variable encompassing all these components would not be able to capture the differential impacts of these variables. For this reason, disentangling political uncertainty into its main components turns out to be crucial.

We could provide many examples where institutions and policies moved in opposite directions when relevant political events happen. This was the case of Greece in 2011 when Prime Minister George Papandreou resigned after accepting the financial receovery plan of the Troika. The turmoil caused in the society by the acceptance of this recovery plan that was considered unfair by a large part of the Greek society led Papandreou to resign. We will discuss the data that we use in Section 1.4, but we mainly focus on experts' evaluations. In our data, the quality of policymaking after accepting the financial plan drastically improved, because experts judged the new economic policy imposed by the European Union and the International Monetary Fund as able to restore long-run economic growth. On the other hand, the price that Greece had to pay for accepting this austerity plan was to loose the government. Greece indeed fell in a period of high political instability. Thus, political stability decreased but the quality of economic policy increased, according to the data.

In the same fashion, Japan also experienced a similar situation in 2012, where political stability slightly decreased against a very strong increase in the quality of policymaking. This happened when Shinzo Abe was elected Prime Minister and started his economic reforms which went under the name ”Abenomics”. Experts judged that Japan considerably increased the quality of its economic policy, despite the fact that political instability did not move much, showing a slight decrease.

Other examples of political events when economic policy increased against a decrease of political stability (or with stability remaining essentially stable) can be found in many other countries. We can cite, among many others, Argentina in 2015, when Macrí was elected; Italy in 2011, when Berlusconi's government collapsed inducing the President of the Republic to form a government of technicians with Prime Minister Mario Monti; Spain and Portugal between 2011 and 2016, when the countries partly recovered through new reforms from the financial crises despite uncertain and unstable political environments.

The opposite situation often happened as well: political stability that increases or stays essentially constant against a deterioration in the quality of policymaking. This was the case, among many others, of Brazil between 2012 and 2013. Political stability did not change, but the quality of the economic policy drastically decreased. In that period, Brazil experienced the corruption scandals of the government of Dilma Rousseff, and the experts did not have any confidence that the government would have been able to implement effective reforms for the country. This translated into a huge deterioration of the rating for the quality of the economic policy of Brazil.

In order to quantitatively corroborate our theoretical analysis, we compute the correlation between these political variables. Since the institutional variable is only available starting from 2008, we provide the correlation between institutions and policies in the period 2008-2016. On the other hand, for the correlations between economic policy and, respectively, political stability, legal and administrative restrictions, and corruption, our sample covers the 25 years in the period 1992-2016. In both cases, our sample comprises 42 countries: 22 developed countries and 20 emerging markets, following the MSCI classification. We present the correlation between policy and institutions over time and across countries. Regarding the former, we compute for every country $k = 1, 2, ..., K$ the correlation between these two variables over time. We then compute the average across countries. As to the latter, we report the time average of the cross-sectional correlation. We present results for both the correlation in levels and in differences. As far as the latter is concerned, denoting with $X$ and $Y$, respectively, the variables describing policy and institutions, we first compute the series of the time differences $X^* = X_t - X_{t-1}$ and $Y^* = Y_t - Y_{t-1}$, and we then compute the correlation in difference on the series $X^*$ and $Y^*$. The rationale is that we aim to check whether an improvement (deterioration) in political instability for country $k$ is statistically associated to an improvement (deterioration) in economic policy for the same country $k$.

This quantitative analysis reported in Table 1.1 strongly supports the main point of this paper. The correlation over time in levels is 0.101 for developed countries and $-0.065$ for emerging markets. Very interestingly, the correlation in time differences is even lower, 0.062 for developed and $-0.070$ for developing countries, highlighting that a change in the performance of country $k$ for political instability is not correlated with a change in the performance for economic policy. Hence, looking at the dynamics of these two variables, we can claim that they do not move together.

Moreover, as a robustness check, we plot the full distribution of the correlation over time for every country. In fact, one might argue that the average correlation is close to zero not because the two variables are indeed low correlated, but simply because the correlation distribution turns out to be bimodal, with some countries displaying very high and positive correlation, and some countries very high but negative correlation. We plotted the full distribution of the correlations over time, showing that it is strongly concentrated around zero, vindicating our point.

We also report the results for the correlations across countries in Table 1.2. The results are similar to those of the correlation over time. As far the correlation in levels is concerned, it is still reasonably low for both developed countries and emerging markets. As to the former, the correlation is 0.525, while the latter present a correlation equal to 0.114. The same reasoning above applies to this case as well: in order to ensure that our results are not driven by a bimodal distribution where the correlation is either high and positive or high and negative, such that the average close to zero due to this effect for which high and positive values and high and negative values cancel each other, we plot the full distribution of the cross-sectional correlation for each time $t$. Results confirm that, still, the distribution is very much concentrated around zero.

Tables 1.1 and 1.2 also reports the values of the correlation coefficients between economic policy and all the sub-components of the institutional variable. Overall, results confirm the main message of this paper: the correlations are always pretty low for all the pairs economic policy-political instability, economic policy-corruption and economic policy-legal and administrative restrictions. As noticed from the aforementioned results, the correlation in differences is again lower than the correlation over time, shedding light on the fact that once we observe an increase (decrease) in the quality of policymaking, we should not necessarily expect an increase (decrease) in political stability, a decrease (increase) in corruption or legal and administrative restrictions.

## 1.3 Related literature: from political science to financial markets

The first step in our analyses consists of precisely define policy and institutions. We build on the work by North (1990), using the definitions of institutions and policies that he coined in his work, for which he won the Nobel Prize. Economic policies are defined as *"specific legislative enactments"*. The quality of policymaking therefore refers to the effectiveness of the fiscal policies implemented by the government to solve the specific problems of a country and to boost its long-run economic growth. On the other hand, North defines institutions as *"the rules of the game of a society, or, more formally, ... the humanly devised constraints that shape human interaction"*. Accordingly, our institutional variable refers to the ineffectiveness of political institutions, due to the three elements that represent its three main components: government instability, weak legal systems and corruption.

In his work, North (1990) aims to explain the failure of economic performance in different countries to converge over time. Implementing an analysis based on rational-choice theory, the author proves that institutional arrangements may lead quite rational actors to behave in ways that are collectively suboptimal. He also sheds light on the fact that efficient markets need supporting institutions that can provide the formal and informal rules of the game of a market economy, allowing lower transaction and information costs and reducing uncertainty. The legal and governmental arrangement as well as informal institutions underpinning an economy influence corporate strategies and thus influence the operations and performance of businesses.

Proceeding along the same path, Pierson (1993) defines two different forces that operate in political science: an institutional force and a public policy force. The former deals with formal governmental institutions and political organizations. The latter influences the allocation of political and economic resources, modifying the costs and benefits associated with alternative political strategies, and consequently altering political development. Indeed, the author claims that there are feedbacks in both directions, since political development and institutions are affected by the type of policy implemented, and the public policy is also affected by the type of institutions.

Furthermore, North (1990) also differentiates between formal and informal institutions. This vindicates the importance to look not only to formal institutions as the government and its stability, but, as we indeed do in this paper, to also focus to informal institutions and their consequences. Some phenomena leading to corruption, for example, can stem from informal institutions, as a generally accepted behavior by a society. This reinforces the need to look at the different aspects that refer to the two components of institutions, both formal (government stability, rule of law) and informal (corruption).

Also Bevan (2004) underscores how important it is to look at the impact of formal institutions, focusing on their impact on foreign direct investments. Most importantly for the purpose of our research, the paper highlights that the literature has treated separately some factors that affect economic performance: government economic policy (Gomes-Casseres (1991)), intellectual property rights protection (Oxley (1999)) and political risk (Henisz (2000)). Famous scholars like Kogut et al. (2002) and Stiglitz (1999) have indeed argued that the establishment of new institutions (as, for example, the transition from the Soviet Union to Russia with the need to build an appropriate legal and institutional structure) is at least as important as more conventional macroeconomic objectives.

Erb et al. (1996) assess the impact of political factors on stock market returns. They analyze the International Country Risk Guide (ICRG) which provides 3 indices of the quality of economic, financial and political factors. However, we can see there the main problem that we want to resolve with our paper. The political index comprises elements which are intimately related to our institutional variable (political terrorism, racial tensions, political party development, quality of the bureaucracy, corruption in government) but also elements that belong to the economic policy variable (economic expectations versus reality, economic planning failures). One of the findings of the paper is that trading strategies using signals from financial and economic ratings produce abnormal returns, but trading strategies based on political rating do not produce abnormal returns. On the contrary, our paper establishes that trading strategies jointly exploiting institutional and economic policy ratings produce abnormal returns that are economically, statistically significant and much higher than the returns that could be attained using either institutional or policy ratings alone. The second step consists of identifying the literature that provides a theoretical link between institutions and policies, analyzing the feedbacks effects that can exist from one to another. Persson (2002) is a benchmark paper in that respect, since the author shows that institutions do shape economic policies, and therefore we cannot neglect the presence of both factors. Pierson (1993) is another masterpiece which explains in detail the mechanism of âĂIJpolicy feedbackâĂİ, according to which there are two forces that influence each other: an institutional force and a public policy force. He talks about feedbacks from one to another, claiming that previous literature did not specify the range of ways in which policies can affect politics, hence they failed to identify important paths of influence. This is particularly relevant for the example that we reported in the previous section regarding the case of Greece. The resignation of the Prime Minister George Papandreou caused by the economic policy implemented and imposed by the Troika is a clear example of the feedback effect from economic policy to political instability. Very interestingly, the author claims that interest groups shape policies, and policies shape interest groups. The organizational structure and political goals may change in response to the nature of the policy programs they confront and hope to sustain and modify.

As a third step, we survey the literature that provides a link between economic policy risk and financial markets. Henry (2000b) studies the impact on the equity market deriving from the government choice to liberalize the stock market. Liberalization of the stock market is a policy instrument that refers to the government choice of allowing foreign investors to buy shares listed on the domestic stock market. The consequence of such a choice, which turns also out to be the motivation for which the government decides to implement this reform, lies in the well established prediction stemming from international asset pricing models: indeed, several works, including Stapleton et al. (1977) and Stulz (1999a, 1999b), prove that in such a framework the cost of equity of the liberalizing country decreases due to the risk-sharing between domestic and foreign investors. Hence, this public policy choice is usually regarded as a good economic policy. Henry (2000) shows that its effect on the stock market is positive: the equity index of the liberalizing country earns abnormal returns of 3.3% per month in the 8-month window leading up to the implementation of such a policy.

In another paper, Henry (2000a) shows that stock market liberalization leads to an investments boom. If capital markets are efficient, prices should reflect all the information available: hence, according to standard financial theory, it follows that much higher investments in the country should be reflected into higher stock market prices, thus higher excess returns.

Perotti et al. (2001) proceed along the same path, studying the impact of a privatization policy on stock market development. The authors associate the sustained privatization program to good economic policy, since this can be seen by investors as a commitment to a market-oriented economic policy. The papers show that, in a later stage after the start of the privation policy, when investors get convinced that the government is committing to a market-oriented policy, the perception of good policymaking increases and there is a positive effect in that the stock market experiences higher excess returns and traded volumes.

La Porta et al. (2002) investigate the economic policy of government participation in finance shares. They analyze how the policy of a government to participate in banksâĂŹ shares affect financial markets. They motivate their analysis by citing the literature about the opportunistic behavior of governments (seeKornai (1979) and Shleifer and Vishny (1994)): politicians would like to control investments by firms for opportunistic rather than social purposes. In this view, a government acquire shares in firms and banks in order to provide supporters with employment, subsidies and other benefits. On the other hand, supporters may provide back to politicians these favors in terms of bribes, political contributions and votes. Such an opportunistic policy (thus considered as bad economic policy) has negative effects: banks ownership by the government leads to misallocation of resources that are detrimental to productivity growth and economic growth. If markets are efficient, standard assumption in financial theory, they are therefore negatively affected by a slow economic growth. The paper also shows that such a negative economic policy has as a consequence slower subsequent financial development. Moreover, the paper describes other opportunistic, thus bad, economic policies that a government may implement. For example, it can provide subsidies to firms or banks directly, encourage banks to engage in politically desirable projects via moral suasion or regulation, in addition to own financial institutions, partially or completely. This last way presents the advantage to having the control on the projects being financed while leaving their implementation to the private sector.

Jensen et al. (2005) is another work that shows how market-friendly economic policies positively affect stock market returns. The authors focus on the Brazilian elections in 2002, won by Lula. The main idea underlying the paper is that the stock market reflects the probability that each of the 4 candidates will win the election and their expected economic policy. The economic policy is evaluated in terms of a number of factors as the preferences of each candidate about external debt, budget surplus, tax policy, trade reform and privatizations. The authors explain the theory for which stock markets should positively react to a market-friendly economic policy. According to financial theory, a stock is nothing but the discounted value of all expected future dividends (Gordon (1959)). Under an economic policy that makes expected dividends higher, stock prices will therefore increase. It therefore turns out that the election of a candidate which is more likely to implement a market-friendly policy that boosts firmsâĂŹ revenues and profits will lead to a better stock market performance.

Very interestingly, the authors point out that any event study that focuses on the effects of political events on macroeconomic indicators lacks the presence of the counterfactual: what would have happened had another President been elected? They mention that most people argue that Reagan economic choices were the main cause of high government deficit, but in that period the US economy was sluggish as well, and we cannot observe how the deficits would have evolved under different economic choices from a different President but under the same weak economic conditions. However, the advantage of looking at the stock market is that stock prices incorporate already the expectation that either of the 4 candidates to the presidency will prevail. Therefore, computing these probabilities and focusing on the economic policies promised by each of the candidates, and checking the stock market reactions is a way to get rid of this problem of the counterfactual.

Bekaert et al. (1997) also shows that liberalizations impact the stock market, increasing the correlation between the local stock market performance and that of the global stock market index. Moreover, Nordhaus (1975) develops a new theoretical model which has become a benchmark work for political scientists. He argues that politicians implement myopic behaviors in that in the second part of their mandate, right before the election, they behave opportunistically in order to be elected. Their policies are therefore distorted from the effective ones that should be implemented. He shows the implications for the unemployment-inflation trade-off.

After having reviewed the literature discussing the relationship between policies and the markets, we now move to survey the literature that studied the link between institutions and financial markets. Bialkowski et al. (2008) provide evidence that the failure to form a coalition with a majority of seats in parliament straight after an election impacts the stock market. More specifically, this institutional instability creates uncertainty in the market which therefore increases stock market volatility. Diamonte et al. (1996) argues that the reduction in institutional ineffectiveness boosts stock market returns. Therefore, stock market returns can be forecasted if the dynamics of future institutional performance can be predicted.

La Porta et al. (1997) shows that countries with poorer investor protections and inefficient rule of law have smaller and narrower financial markets, referring both to the equity and the debt markets. The channel identified by the paper is that a better legal environment positively affects the size and the extent of the financial markets, in that the potential financiers are protected against expropriation from the entrepreneurs.

Busse et al. (2007) shows that more political stability and better rule of law positively affect foreign investments inflow. Knack et al. (1995) show that legal and administrative restrictions, political instability and corruption negatively affect economic growth and investments. The paper provides evidence of the fact the magnitude of the effects stemming from these factors on economic growth is high, similar to that of education. Last but not least, Barro (1991) shows that countries with higher political stability experience higher economic growth. Several other papers studying the linkages between institutions, politics and financial markets can be cited: Forsythe et al. (1992) shows that the market reacts to political elections, and Feng (1997) explains that democracy and political stability foster economic growth, and the other way around: economic growth creates a fertile environment for the establishment of democracy.

We aim to contribute in this literature by showing a crucial element: policy and politics do not go together. They are very different aspects, as theoretical political scientists have shown. Moreover, we provide empirical evidence of the low correlation that these two variables have in the data. Disentangling them becomes therefore very relevant, in order to study the differential impact that they have on financial markets. We are going to show in the next sections how important and beneficial it can be to disentangle economic policy from institutions, and in particular policy from political instability.

## 1.4 Data

One of the innovative points of this research is to find effective measures of our four political variables, which, *a priori*, are not quantitative variables. In this paper we deal with two main macro-levels. The first one differentiates between economic policy and institutions. The second one further disentangles institutional effectiveness into political instability, corruption, and legal and administrative restrictions.

Regarding the quality of policymaking, data come from the IFO World Economic Survey, the details of which are described below. As far as institutional effectiveness is concerned, a score for each country is computed and provided by the EIU, acronym for "Economist Intelligence Unit", owned by The Economist. One of the key and innovative elements of this research is to highlight that politics and policy are completely different variables, not even very much correlated and also priced differently. However, to reach such a conclusion, we have to make sure that these two variables, in the way they are constructed, actually look at completely different aspects without any overlap. This is indeed ensured by the fact that the IFO polls respondents to evaluate very precisely how the economic policy of the government is affecting the country's economy, and whether the former represents a problem for the latter. On the other hand, the institutional score provided by the EIU is computed by weighting some aspects that are related to the political life of each country and are totally uncorrelated with the economic policy of the government. Among the factors taken into consideration, the highest weights are given to governability, the probability of extreme political events and the consequent turmoil, and government commitment to pay. It is also precisely stated that quality of economic policymaking and fiscal policy flexibility are not considered to construct this institutional score. It therefore turns out that out two measures of policy and institutions, as employed in this paper, do not present any overlap and clearly analyze very different aspects of the channel between politics and financial markets.

The IFO survey provides comparable statistics on global economic confidence. The IFO polls, semi-annually, economic experts from international and national organizations worldwide requiring an assessment of the main economic indicators. 45% of the economic experts interviewed work for international corporations, 15% for banks and 5% in the insurance sector. 10% work in economic research institutes, 10% for chambers of commerce, and 5% for consulates and embassies. The remaining 10% are affiliated with international organizations as, for instance, OECD and IMF, as well as with foundations, media and press. The IFO selects only highly qualified people as respondents: they are all in a leading position or they are occupied with economic research within their institution. The participation to the survey is voluntary. In return, participants only get exclusively detailed and timely results of the survey, such that pure professional interest in the surveyed topic and the survey results are the sole incentive for the experts' participation. From 2002, around $1,000$ economists from more than 90 countries have been participating to the survey. Hence, the high quality of these data, ensured by the procedure outlined above, has motivated our choice to rely on the IFO reports.

Concerning the interpretation of these country-specific ratings, the policy index can range from 0 to 100: higher scores are associated to a worse policymaking. On the other hand, the institutional score computed by the Economist Intelligence Unit can range from 0 to $+\infty$, with, as above, higher values denoting a worse performance of the country in that respect, *i.e.* higher institutional ineffectiveness.

As to the second macro-level, we decompose institutional effectiveness into political instability, corruption, and legal and administrative restrictions. We measure political instability through the IFO surveys as well. This country-specific index can range between 1 and 9: higher ratings are associated to more political stability, thus a better performance of the country in that respect. The same reasoning applies to legal and administrative restrictions. This indicator is also provided by the IFO, and it can range between 1 and 9: higher scores reflect a lower level of restrictions, hence a better performance of the country. Data provided by the IFO, concerning economic policy, political instability, and legal and administrative restrictions, are at semi-annual frequency and they span the twentyfive years from 1992 to 2016.

The policy index can range from 0 to 100. On the other hand, data about corruption are provided by Transparency International with the label of "Corruption Perceptions

Index". They define corruption as *"the abuse of entrusted power for private gain, and can be classified as grand, petty and political, depending on the amounts of money lost and the sector where it occurs"*. Intimately related to corruption and used to construct the index is transparency, which means *"shedding light on shady deals, weak enforcement of rules and other illicit practices that undermine good governments, ethical businesses and society at large"*. It is apparent even from its definition that corruption should be disentangled from economic policy, political instability, and legal and administrative restrictions. The data provided by Transparency International cover the period 1996-2016 and are at annual frequency, whereas the data of institutional ineffectiveness provided by the EIU are at quarterly frequency and they are only available for the period 2008-2016.

In all our regressions, we control for the effects stemming from the most relevant macroeconomic variables. We download from Datastream data for the following variables. We have quarterly data for GDP growth rates with respect to the previous quarter, unemployment rate over the GDP, interest rates on 10-year government bonds and 3-month interest rates. We construct the slope of the term structure as the difference between these long- and short-term rates. We have data at annual frequency for public debt and primary balance, both as a percentage of the GDP. We make use of the MSCI Investable stock market index for each country. CDS data and foreign exchange rates are also available on Datastream.

Our sample comprises 42 countries worldwide. We follow the classifications provided by Morgan Stanley Capital International, dividing our sample into two groups: developed countries and emerging markets. Following Lustig et al. (2011), we present results for developed markets and all markets together. The developed countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom, Canada, USA, Hong-Kong, Japan, Australia and New Zealand. The emerging markets are Czech Republic, Hungary, Poland, Russia, Brazil, Chile, Colombia, Mexico, Peru, Israel, Turkey, China, India, South Korea, Malaysia, Philippines, Taiwan, Thailand, Egypt and South Africa.

## 1.5 Empirical investigation

In this section we start investigating the impact of these political factors on the three major financial markets: the stock market, the CDS market and the foreign exchange market. We aim to assess the differential impact of these disentangled political variables on each of the aforementioned financial markets, in order to understand if these variables are priced, in which markets they have the strongest impact, and which is the direction of the impact.

For the sake of simplicity, we are going to analyze the impact of economic policy and political instability only. Our choice is motivated by the need to find a unique proxy of institutional effectiveness without overcomplicating the analysis. Political instability is the most relevant component of institutional effectiveness, and therefore we focus on instability as analyze its differential impact with respect to economic policy.

We present our empirical results in three subsections, each of which dedicated to a specific market: stock, CDS and foreign exchange. We nevertheless follow the same procedure in each market. To start with, we divide our sample in quintiles, classifying the countries in these five clusters according to their economic policy score. Second, we present the average stock market return (CDS spread, currency depreciation rate) for each group, aiming to establish a clear relationship between policy scores and average stock returns (CDS spreads, currency depreciation rates). Third, following Belo et al. (2013), we compute the statistical difference in stock average stock returns (CDS spreads, currency depreciation rate) between the last and the first group, *i.e.* between those countries with best economic policy and those with worst economic policy, in order to understand whether there is enough heterogeneity in the countries in the different quintiles.

Fourth, as far as the stock and foreign exchange markets are concerned, we create long-short strategies based on these political variables (which will be described in detail in what follows) and we test their performance on the most relevant asset pricing model. We aim to assess whether these strategies loading on our two political variables and exploiting the low correlation between the latter can generate abnormal returns that are statistically and economically significant. After having controlled for risk, the sixth step consists of running panel regressions to check that our political variables still play a relevant role on the stock, CDS and foreign exchange markets even after controlling for the most important macroeconomic variables.

Needless to say, we do the same for the univariate sort according to political instability. Most importantly, we then sort the countries according to a bivariate criterion such that we analyze those countries satisfying two conditions at the same time: in particular, we are interested in those countries performing well in both policy and instability, and those displaying jointly a bad score in both indicators. The bivariate sort turns out to be crucial for the message conveyed by this paper: if economic policy and political instability both play a relevant role in affecting the financial markets, and if they display low correlation, the countries characterized by high-quality (low-quality) policymaking are not necessarily those with high (low) political stability. Hence, combining these two indicators and selecting countries that are *jointly* characterized by good policy and high stability should be beneficial.

### 1.5.1 Analysis on the CDS market

We start our investigation from the CDS market. As mentioned above, we first create quintiles classifying each country in a group according to the value of economic policy score, political instability, corruption, and legal and administrative restrictions. Table 1.3 reports the average CDS spread of each quintile for developed countries, emerging markets and all countries together. Indeed, looking at all markets together, CDS spreads grow monotonically from the best quintile to the worst quintile. Results are very robust across all our four political variables. The interpretation does not change when looking at developed countries and emerging markets alone. Worse policies, higher political instability, more corruption and higher levels of legal and administrative restrictions are associated to higher CDS spreads.

There appears to be a huge heterogeneity between the groups: the average quarterly CDS spread of the top quintile is only 70.58 basis points when sorting according to economic policy, while the bin incorporating those countries with the worst economic policies reaches an average value of the CDS spreads equal to 242.78 basis points. The same applies to political instability, where the most stable countries have an average spread of 56.02 basis points against 305.64 for the countries with the highest political instability. Likewise, the least corrupted countries display an average CDS spread of 48.44 basis points, whereas the most corrupted ones touch 228.78. The same interpretation can also be inferred from legal and administrative restrictions, where the countries with the lowest values of restrictions display an average spread of 82.82 basis points, against 261.05 for those countries characterized by the highest level of restrictions.

It is worth underscoring once more that the result of the monotonicity is impressive. Sorting according to each of the four political variables produces a monotonic increase in CDS spreads, from the best countries to the best ones. This is a result which is interesting from an *economic* viewpoint. The next logical step consists of testing whether the best and the worst quintile display a difference that turns out to be *statistically* significant. Tables 1.4 and 1.5 reports the results of such a test. Looking again at all markets together, the difference in CDS spreads between the worst and best quintile is 172.20 basis points for economic policy, 249.62 for political instability, 180.34 for corruption and 178.23 for legal and administrative restrictions. These differences are all significant at the 1% significance level: the corresponding t-stats are 11.01*** for policy, 8.59*** for stability, 13.75*** for corruption, and 8.43*** for restrictions.

So far, we have shown that univariate sorts according to each of our four political variables produce a strong heterogeneity in average CDS spreads, with the best countries for these political indicators displaying significantly lower spreads than the worst countries. The main point of this paper is to show that policy and politics are low correlated, both conceptually and quantitatively. In order to reinforce this point, we run a bivariate sort according to two political indicators at the same time. As previously mentioned, we focus on political instability as the main component of institutional effectiveness. Nevertheless, all results hold even when replacing political instability with corruption or legal and administrative restrictions.

Table 1.6 reports the results of a bivariate sort according to economic policy and political instability. We construct four group of countries. The first one comprises those countries falling into the top 20% for economic policy and top 20% for political instability at the same time. Those countries belonging to the intersection of these two sets, best quintile for policy and best quintile for instability, display an average CDS spread over time of only 57.72 basis points. Likewise, the average spread of those countries belonging to the intersection to the last quintile with worst policies and the last quintile with highest instability reaches 568.86. It is crucial to underscore how this value is much higher than the average CDS spreads of each of the two univariate sorts for policy and stability, which were, respectively, 242.78 and 305.64 basis points.

This is key, because it tells us that in the bivariate sort the average CDS spread spikes with respect to the two univariate cases. The interpretation is straightforward: since policy and stability display low correlation, the countries characterized by bad policy are not necessarily those with high political instability. Often, this will not be the case. As a consequence, since both policy and stability are priced (differently) by the market, then picking those countries with bad policy *and* high instability leads to a spike in CDS spreads. Furthermore, our point is reinforced by the fact that there are countries that belong to the best group for policy and to the worst 20% group for stability, and also *vice versa*, meaning that these two political indicators do not have any strong and positive dependence.

As a robustness check, Table 1.7 reports the results of the same analysis but where we form three groups only, instead of dividing the sample into quintiles. Exactly as before, those countries belonging to the intersection of the two sets of worst policy and worst stability display an average CDS spread that is 312.14, higher than the level reached with each univariate sort. Moreover, to corroborate the results of our analyses, 312.14 is significantly lower than 568.86, the previous level obtained when dividing the sample in quintiles. This is exactly what one would expect, since enlarging the worst group to the last 33% instead of the last 20% means that we incorporate countries with slightly better policies and higher stability, thus reducing the overall level of the CDS spread. Table 1.7 confirm that the same results can be obtained when considering developed countries alone.

Our last step is to investigate whether economic policy and political stability do still play a relevant role even when controlling for the most relevant macroeconomic variables that could affect CDS spreads. Tables 1.8, 1.9 and 1.10 report the results of the regressions of quarterly CDS spreads on economic policy, political instability and the macroeconomic factors that represent our control variables. Table 1.8 shows the results obtained when including all the countries in our sample, whereas Table 1.9 reports the results for the sub-sample of emerging markets and Table 1.10 refers to developed countries.

We propose five different model specifications. First, we regress CDS spreads on economic policy by itself. Second, we regress CDS spreads on political instability only. Third, we consider a two-regressor model where we include both policy and instability. Our fourth model focuses only on the control variables, regressing CDS spreads on the macroeconomics factors alone. The fifth model describes the most complete results, where we include our target variables, policy and stability, in addition to the control variables. In all model specifications, we include country fixed effects in order to control for time-invariant and country-specific unobserved factors that may impact decisively the results. As an illustrative example we could cite the weakness of the banking sector. It is not included in our explanatory variables, but in certain countries like Italy, Spain, Portugal and Greece, it could have a relevant impact on sovereign default probabilities and CDS spreads. In other countries there could be other country-specific factors that we omit in our model specifications and that can be control for by adding the country-specific fixed effects.

In addition, in order to make our results more robust, in every model we bootstrap the standard errors to control for the small sample issue and any dependence in the data. We run $5,000$ iterations for each model. In addition, standard errors are always robust, estimated through the Huber-White sandwich matrix. Moreover, in order to fully disentangle the impact of economic policy from that of political instability, we apply the following procedure. First, we regress political instability on economic policy. Second, we save the residuals of the regression in the first step. Indeed, we save that part of political instability which is orthogonal to economic policy. In other terms, we make use in our regressions of that political instability which is not caused by shocks to economic policy. In this way, we make sure to fully disentangle these two political factors.

Results are striking. Both economic policy and political stability are always strongly significant, in all model specifications, at the 1% confidence level. In the univariate regression, economic policy displays a t-stat that attains 4.49***, in the second model where we regress CDS spreads on policy and stability, the former has a t-stat of 4.70***, and even when controlling for the macroeconomic variables it stays strongly significant with a t-stat of 3.33***.

The coefficient is also economically significant. In the most complete model with all the control variables, considering all the markets together, the $\beta$ of economic policy is around 0.5. Considering that the policy score can range between 0 and 100, under the assumption that country scores are uniformly distributed, in order to step from the lowest quintile to the first group characterized by the best policies, it would take an improvement of at least 60, moving up from 20 to 80, in order to reach the best quintile. Accordingly, this would imply a reduction of the CDS spreads of 30 basis points. Just by significantly improving the quality of the economic policy it is therefore possible for a country to reduce remarkably the average CDS spread and thus the default probability. Needless to say, this has huge implications also on the cost of debt for a country. Overall, our findings suggest that worse economic policies and higher political instability get translated into higher CDS spreads, meaning higher riskiness of the country.

Political instability is also significant at the 1% level in all model specifications. In the univariate case its t-stat attains −3.05***, in the bivariate case it becomes −3.32***, and in the model with all the control variables it reaches −3.83***. Two points are worth mentioning. First, these results shed light on the fact that *both* economic policy and political instability are priced. Second, our findings are very robust to all model specifications and they apply to developed countries as well as all countries together. The only small exception concerns the developed countries, the results of which are reported in Table 1.10. Policy is still always significant. However, stability is significant in the univariate and bivariate cases, but it then becomes collinear to unemployment, which plays a crucial role in driving CDS spreads. Nevertheless, our analyses also show that when orthogonalizing unemployment and stability, then the latter becomes strongly significant at the 1% level. The orthogonalization is performed by regressing unemployment on political stability, and then saving the residuals, *i.e.* the part of unemployment that is not due to shocks to political instability. The interpretation is the following: shocks to political stability can affect the economic environment and the unemployment rate, and when we isolate the unemployment rate that does not depend on these instability shocks, then the latter becomes statistically significant. This finding vindicates again the message of this paper: policy and stability do matter for financial markets. If we isolate the shocks that these variables might have on the economic environment in order to eliminate any collinearity problem, then the net effects of policy and stability becomes even more evident.

### 1.5.2 Analysis on the foreign exchange market

We now move to describe the results of the forex market. We follow the same procedure applied before when dealing with the CDS market. To start with, Table 1.11 reports the annual depreciation/appreciation rate of the local currencies of the countries in our sample with respect to the US dollar for each of the quintiles sorted according to our four political variables. Considering all markets together, it is impressive that we still get a monotonic relationship between our political variables and the depreciation rates of the currencies.

We focus here on economic policy and political instability. The first finding that can be inferred from Table 1.11 is that worse economic policies and higher political instability are associated with a strong depreciation of the currency with respect to the US dollar. The quintile with the countries characterized by the best policies experienced an average annual depreciation rate of $-1.02\%$, against a value of $-12.94\%$ fo the worst quintile. Regarding political instability, the effect is even stronger, since the best group displays a depreciation rate equal to $-0.72\%$, while the worst quintile attains $-17.62\%$. The differences between the worst and best portfolios are significant at the 1% confidence level. Furthermore, we also investigated the results of a bivariate sort where we select those countries that display the worst policies *and* the highest political instability. Exactly as in the case of CDS explained in the previous subsection, this group is associated with higher depreciation rates with respect to the US dollar.

So far, our story is very much consistent with our findings referred to the CDS market. In order to go further, we now test the performance of our portfolios against the most relevant asset pricing models. In the univariate cases, we form five portfolios according to, respectively, economic policy and political instability. We then create a long-short strategy where we go long the countries with the best policies (highest stability) and we go short the countries in the last quintile, *i.e.* those with the worst policies (highest instability). We rebalance our portfolios every six months because these two political indicators are available at semi-annual frequency. In the bivariate sort, our strategy goes long the countries belonging to the intersection between the sets of best policies and highest stability, and it shorts those countries falling in the intersection between the two groups of worst policies and highest instability.

We test the model against the factors postulated by the literature. Following Lustig et al. (2011), we employ two risk factors which are specific to the currency market. One is a common factor and the other one is a global factor. The authors identified a *"slope factor"* in exchange rates, which is based on the empirical evidence that the exchange rates of high interest rate currencies load positively on this factor, while those of low interest rate countries load negatively on it. To be consistent with Lustig et al. (2011), we call this factor HML ("high minus low", referred to the level of currency interest rates). The second factor is the average excess returns for an investor who buys the foreign currency in the forward market at time $t$, and who sells it in the spot market at time $t+1$. Lustig et al. (2011) label this factor RX, and it is constructed as the average excess returns for all countries.

This is the benchmark asset pricing model for the forex market. Therefore, we test our strategy returns on each of these two factors separately, and both of them together. Moreover, as a robustness check, we also test the world CAPM, the three-factor and five-factor international Fama-French models, the international Carhart model, one model with all the factors of these four last models together, and a last model including all the factors from the former eight asset pricing models. We report the results in Table 1.12. Our findings are again impressive. In the univariate case where we sort according to economic policy, our strategy, which buys the currencies of the countries with the best economic policies and short-sells those of the countries characterized by the worst economic policies, produces an annualized alpha equal to 11.42%, with t-stat 3.89***. Adding all the other six factors of the models usually employed for stocks does not change the results: the alpha reaches 12.47% with t-stat 3.63***.

The same reasoning applies to political instability, where results become even stronger. In the univariate sort according to political instability our long-short strategy produces an annualized alpha equal to 18.45%, with t-stat 4.20***. Most importantly, the bivariate sort, once again, produces the best results. The annualized alphas spike to 32.66%, with t-stat 4.21***. These results are impressive from an economic viewpoint and very strong and robust from a statistical perspective. Including all the factors of all the other asset pricing models does not change the interpretation and the message that we can infer. Regarding the univariate sort on political stability, the alphas are 20.43% with t-stat 3.85***. Concerning the bivariate sort on policy and stability, the alphas attain 36.33% with t-stat equal to 3.97***. Moreover, Table 1.12 shows that these findings are very robust across all model specifications.

As with the CDS market, our last step consists of running panel regressions in order to check whether the most relevant macroeconomic variables can erase the effect conveyed by our political factors. We report in Table 1.13 the results of all the regressions. Economic policy is always significant across all model specifications, with t-stats equal to 5.24*** for the regression with policy only, 5.19*** for the regression with policy and stability, and 3.70*** when including all the macroeconomic variables as well.

Political instability plays a very important role as well. It is significant at the 1% level in the model with stability only (t-stat −2.97***) and when including economic policy as well (t-stat −3.57***). Interestingly, it is strongly significant when including all the other regressors but long term bond. It becomes collinear to long-term bond, making its beta non-significant anymore. However, when including only short-term rates and all the other regressors, it remains significant at the 1% level. Political instability appears to be correlated to long-term bonds, such that an increase in instability strongly affects the 10-year government bond, which experience an increase in their interest rate. This is reasonable, since political instability can well be a factor impacting the performance of a country, which is incorporated into long-term rates. Overall, our results suggest that economic policy and political instability are priced in the forex market as well. Worse economic policies and higher political instability have a huge effect on currency depreciation rates.

### 1.5.3 Analysis on the stock market

The third market that we analyze is the stock market. We proceed along the same path traced in the previous two subsections. To start with, Table 1.14 reports the values of the annualized returns of each of the quintiles when the countries are sorted according to our four political indicators. We express all stock market returns in US dollars. We classify each country to one bin according to each of our four political variables. Because of the data frequency, we rebalance the portfolios every six months for policy, stability, and legal and administrative restrictions, whereas we rebalance every year for corruption.

Table 1.14 analyzes developed markets and shows that we still obtain perfect monotonicity from the worst to the best quintile for policy, restrictions and corruption. The interpretation does not change for political instability, where we do not get perfect monotonicity but still there is a clear increasing trend in stock market returns when moving from the worst group to the best bin (group 4 displays a return that is slightly lower then the second and third group, despite the fact that the best quintile performs much better than the worst one). To provide the reader with an example, the monotonicity achieved by economic policy is enlightening. The group that comprises the countries with worst economic policies display a return equal to $-0.36\%$, which becomes 3.80% for the second group and 5.87% for the quintile in the middle of the distribution. Then, moving up to the second-best group the annualized return increases to 6.55%, attaining 8.76% with the group that comprises the countries with the best economic policies. As shown by Table 1.14, the results are robust across all our four political variables.

The second step consists of assessing whether this heterogeneity translates into a statistically significant difference between the last group and the first one. Table 1.15 reports the difference between the average difference between the two groups. Following the same approach as with the CDS and forex markets, we test if the time-series of the average quarterly returns of the best and worst groups. The difference is 9.11% for economic policy, with a t-stat of 4.13***. The difference is statistically significant at the 1% level also regarding political instability. The countries with best economic policies earn an average return of 8.31% in excess of the return of those countries with the worst economic policies. The corresponding t-stat is 3.41***. The same conclusion can be inferred from corruption: the difference in quarterly average returns between the least corrupted and the most corrupted countries is equal to 9.09%, with a t-stat of 2.98***. The heterogeneity seems weaker for legal and administrative restrictions, but still the monotonicity result holds and the difference between the best and worst group is statistically significant (the difference is 3.67% with t-stat 1.92*).

Exactly as for the forex market, we now focus on policy and stability, and we test the profitability of an investment strategy that goes long the countries with best economic policies and goes short the countries with worst economic policies. We repeat the same analysis for the univariate sort according to political instability, and we evaluate the performance of the same long-short strategy where the countries are sorted according to a bivariate criterion based on policy and stability. We track the performance of the strategy and test its returns against the most important asset pricing models applied to the stock markets: CAPM, three-factor Fama-French, five-factor Fama-French, Carhart, and a model that incorporates all the factors of the previous models.

Table 1.16 reports the results of such analysis for developed markets, which are striking. Sorting according to economic policy produces alphas that are economically high (on average $5-6\%$ annualized across all the models) and statistically significant at the 1% level. Sorting according to political instability yields lower alphas, but still economically and statistically significant.

The most interesting result stems from the bivariate analysis. Once again, if policy and stability were not correlated, then we would expect that buying only those countries belonging to the intersection between the group of best policies and highest stability, and short-selling those at the intersection between the sets of worst policies and highest instability, yields higher returns with respect to the univariate case. The rationale behind it is that since policy and stability display low correlation, several countries will belong to either the group of best (worst) policies or that of best (worst) stability, but not to both of them.

Table 1.16 shows that exploiting the information embedded in both indicators is indeed beneficial. Considering the three-factor Fama-French model, the annualized alpha spikes and reaches 10.36%, with t-stat 3.10***. Results are very robust across all model specifications. Alphas still remain very high economically and statistically, attaining 9% on average and being statistically significant at the 1% level. These findings support again a performance (cash-flow) story: those countries that implement good economic policies and that display high political stability perform better on the stock market. Our results are impressive, in particular with reference to the bivariate sort, which clearly shows how crucial it is to disentangle policy from stability and exploit all the information embedded in those two indicators.

Table 1.17 reports the results for the alphas referred to all markets together. We remove Russia and Brazil as in the top 3 of the most volatile countries in our sample. As expected, alphas are smaller when including very volatile markets and the emerging countries in our sample. Nevertheless, it is interesting to notice that the bivariate sort still generates abnormal returns that are significant both from a statistical and an economic point of view. Policy and stability need to be combined in order to find robust alphas, as the main message of this paper suggests. Alphas are around 5% per year and are significant at the conventional levels.

To conclude our analyses, we present the results of the panel regressions models. We focus on both *(i)* realized returns, and *ii)* expected returns. In the former case, we regress stock market returns on contemporaneous values of our political indicators and the control macroeconomic variables. In the latter case, we go further and we try to explain future market returns out of sample. For expected returns, we proceed as follows. We take as a benchmark the publication date of our political indicators. At that date, the country ratings for our political variables become available and therefore are known to the investors. Our dependent variable is stock market returns in the subsequent quarter, starting from the publication date. Our explanatory variables are these political ratings, available when they are released, as well as all the control macroeconomic variables, again lagged once with respect to stock market returns.

We start by discussing the results referred to expected returns. Tables 1.18 to 1.21 clearly point out that both policy and stability play a crucial role in driving stock market returns. Results are very robust across all model specifications, both for developed countries and emerging markets, and when including country fixed effects only and country and time fixed effects together. The main result is that, for developed markets, policy and stability are always statistically significant at the conventional levels. Hence, these IFO ratings can be very useful to predict future stock returns. Moreover, the R-squared of the regressions when considering both country and time fixed effects attains 65%, which is remarkably high for predictive regressions. When considering all markets together, the effect of the noise and volatility introduced by emerging markets becomes evident. With country fixed effects policy and stability stay strongly significant, whereas with time fixed effects they lose their statistical significant, even if their effect is still economically significant.

Moving to analyzing realized returns, Tables 1.22 to 1.25 (fore developed countries) and Tables 1.26 to 1.29 (for all markets together) show what one would expect: results are even stronger in this case than with expected returns. Our findings are consistent when replacing political instability with the orthogonalized stability (with respect to economic policy), and when considering only country fixed effects or including also time fixed effects in addition to country fixed effects. Results are striking in that our political variables are always significant at the conventional levels, and, with the most complete models including all the macroeconomic control variables, economic policy and political instability are consistently significant even at the 0.1% level.

These findings confirm that better policymaking and high political stability are rewarded by the market. In particular, when considering the most complete models with all the control variables and taking into account both country and time fixed effects, results show that there is a strong economic effect. Concerning economic policy and focusing on developed markets, there is strong incentive for the government to improve the economic policy and to promote more political stability. The betas of the regression for these two political variables reveal that if a country remarkably improves its policy, moving from the last quintile of countries to the first quintile, experiences a stock market returns that is around 8% higher (per year, than before. Likewise, if a country jumps from the last quintile to the best one for its political stability, the effect is even stronger: the stock market increases its performance by approximately 12% per year.

In the same fashion, studying less extreme cases than the drastic improvements in policy and stability, we can also claim that moving up from a quintile to the next one translates into an increase in stock market performance equal to 2% per year regarding policy and 3% per year concerning political instability. These are results that are significant also from an economic viewpoint. If we focus on all markets together we obtain even stronger results. Moving from the bottom to the top translates into an increase in stock market performance of around 14% per year regarding policy and 23% per year for stability. This means that moving up from a quintile to the (better) consecutive one is associated to an outperformance of. approximately, 3.5% per year for policy and 6% per year for stability.

## 1.6 Channel identification

The last logical step in our analysis consists of identifying and explaining the channel through which better economic policies and more efficient institutions *positively* affect the stock markets. In our analyses we have shown that a better economic policy and higher political stability display high explanatory power for both realized and expected returns. Our findings are consistent with a cash-flow story: in a politically stable environment with good policymaking, firms undertake more long-term projects, foreign investors are more willing to place their money in that country, and the economy grows at a faster pace.

This view is consistent with previous findings in the literature. There are several papers that investigated the role played by political stability and economic policy on economic growth. Among others, Alesina et al. (1996) show that the growth rate of the economy is significantly lower in countries with high political instability. Regarding economic policy, Easterly et al. (1993) underscores the relevance of the fiscal policy as one of the main drivers of economic growth. Consistently with the empirical evidence provided by these papers, countries characterized by high political stability and good policymaking should show higher growth rates of their gross domestic product.

In order to test our cash-flow story, we run panel predictive regressions of stock market returns of future growth rates of GDP over our political variables and all the control variables. We repeat the analysis for different horizons. We compute future GDP growth rates for the next 3 months, 6 months, 1 year, 2 years, 3, years, 4 years and 5 years. We aim to investigate whether current levels of political instability and current quality of policymaking help predict future growth rate of the economy. In order to fully disentangle the impact of policy from that of stability, getting rid on any feedback effects between these two political forces, we orthogonalize stability from policy as previously shown. Results are nevertheless robust when employing the original measure of stability instead of the residuals of its regression on economic policy.

Table 1.30 reports the results of these predictive regressions with country fixed effects, and Table 1.31 when considering country and time fixed effects. Results confirm the strong impact of our political variables on future growth rates of the economy, since both policy and stability are almost always significant at the 1% level. Interestingly enough, the effect of both policy and stability grows with the horizon of the predictive regressions. It reaches a peak around 3-4 years ahead, then the effect is still very significant but starts to slightly decline. These findings confirm that our political variables have a strong effect on future growth rate of the economy. As expected, consistently with a cash-flow story, better policymaking and higher political stability translate into higher future growth rate of the GPD.

In order to corroborate our analysis, we employ other variables that are clear indicators of the growth of the economy and that can be correlated to the cash-flows produced by firms. The first one is industrial production. We obtain country-specific data for the industrial production index from Datastream. The main difference with respect to GDP growth rate is that the latter incorporates also the public sector, which is independent of private firms. Hence, in order to find measures that are even more closely related to firms' cash-flows, we run the same predictive regressions with industrial production future growth rates as dependent variable. Tables 1.32 and 1.33 report the results when considering only country fixed effects and when adding also time fixed effects. The results are consistent with the analysis on GDP growth rates. Both policy and stability are almost always significant at the 1% level.

In order to offer to the reader a quantitative interpretation of our findings, let us focus both on GDP and industrial production growth rates with the 3-year horizon. Regarding the former and focusing on policy, we can claim that when a country jumps from the worst quintile all the way up to the best quintile, it will experience, everything else equal, an increase in its 3-year GDP growth rate of 3.6%, meaning an average increase higher than 1% per year. In the same fashion, moving from the worst to the best quintile for political stability would translate into an increase of approximately 5% in the 3-year GDP growth rate, meaning an average annual increase higher than 1.5% per year. Again, these numbers are economically significant, not only statistically significant. Good policymaking and a stable political environment pay off. Likewise, regarding industrial production, the average increase in the 3-year growth of industrial production thanks to the same improvements described above would be around 3.3% for policy and 5.6% for stability.

As an additional robustness check, we also employ another measure that is closely related to the cash-flows produced by firms: aggregate dividend yield. We obtain aggregate dividend growth rate, at different horizons exactly as before, by simple mathematical manipulation starting from the the stock market index with and without dividends. More specifically, the dividend growth rate between time $t-1$ and time $t$ turns out to be

$$\frac{D_t - D_{t-1}}{D_{t-1}} = \frac{R_t^{(with)} - R_t^{(without)}}{R_{t-1}^{(with)} - R_{t-1}^{(without)}} \cdot R_{t-1}^{(without)} - 1, \tag{1.1}$$

where $R_t^{(with)}$ and $R_t^{(without)}$ denote, respectively, the *gross* returns of the stock market index including and excluding dividends between time $t-1$ and time $t$:

$$R_t^{(with)} = 1 + r_t^{(with)}. \tag{1.2}$$

The results are reported in Tables 1.34 and 1.35, respectively taking into account country fixed effects and country and time fixed effects. Our political variables display a relevant predictive power also with aggregated dividends. The magnitude of the effect is very similar to the aforementioned results for GDP and industrial production. These findings point again in the same direction, supporting a performance story where the focus is on firms cash-flows. A politically stable country with good policymaking is a fertile enironment where firms can produce, export their goods and increase their cash-flows. Everything else equal, when firms produce more cash-flows, then their stock price will rise as per basic finance theory, since the price of a stock is nothing but the discounted value of all its future cash-flows under the risk-neutral probability measure. Accordingly, we can conclude that our cash-flows story is strongly vindicated by our robustness checks, and it is not sensitive to the particular measure of the growth of the economy and the cash-flows produced by firms that is employed.

## 1.7 Conclusion

In this paper we have shown how crucial it is to disentangle two different political variables that affect financial markets: the quality of economic policy and the effectiveness of institutions. We have shown that the institutional variable can also be further disentangled into three main components: political instability, legal and administrative restrictions, and corruption. The key message of our paper is that policy and institutions do not move together. From a theoretical point of view, they are very different concepts, as political scientists have argued. From an empirical perspective, we have shown that they display very low correlation in our sample that comprises 42 countries (22 developed and 20 emerging markets) in the period 1992-2016.

The implications of these low correlations are crucial. First, all the papers in the extant literature that assess the impact of politics on finance lack precision in the identification of which factors are actually driving the results. Some countries might display high political stability but suffer from the absence of an effective and convincing economic policy. The reverse can hold as well: some countries that are judged to be characterized by good policymaking can be characterized by instability of the political institutions and/or political turmoil. In this paper we have reported many examples from all over the world where both these two situations happened.

This is absolutely key, because many times policy and politics point in different directions and would give different interpretations about the performance of a country. In all these situations, analyzing a general porte-manteau political variable neglecting its components would fail to identify what are the reasons for which we observe certain dynamics of the financial markets. We have provided several famous real-life examples where economic policy performance went up but institutional performance went down, and *vice versa*. We have also supported our argument by means of some literature in political science which reinforce our theory.

After having checked that our theory is grounded not only conceptually but also in the data through our correlation analyses, we have analyzed the impact on the three most relevant financial markets: the stock, CDS and foreign exchange markets. We have shown that countries with a better economic policy, higher political stability, lower levels of corruption and restrictions experience significantly lower CDS spreads, a lower depreciation rate with respect to the US dollar, and higher stock market returns.

Most importantly, we have shown that sorting all the countries according to a bivariate criterion that hinges on economic policy and political instability can be beneficial. Those countries belonging to the intersection of the two sets of groups displaying high political stability and good economic policy display significantly lower CDS spreads, lower depreciation rates for their currencies and outperform the other countries on the stock market. This is due to the low correlation between policy and politics, and reinforces our main point of the need to disentangle these two variables and exploit the information embedded into both of them.

Our research has several relevant policy implications for investors and governments. Regarding the former, we have shown how to create long-short trading strategies able to beat the market and generate huge abnormal returns with respect to all the main asset pricing models existing in the literature, both in the stock market and in the foreign exchange market. Concerning the latter, we have proceeded to shed light on how important it can be for a government to improve its economic policy and for a country to create efficient and stable institutions. We have quantified the remarkable impact that these two variables have on stock returns, currency depreciation rates and default probabilities embedded in CDS spreads. This also has considerable implications on the cost of external financing for a country, which is intimately related to the fiscal discipline of a country and how much it can spend for its citizens. For all these reasons, we can claim that our research can be of interest for the society as a whole.

The work described in this chapter led to the need for a theoretical model, which has been developed during my PhD and will be published after the thesis. This paper will be co-authored by myself and the Professors with whom I have been working on this model, Professor Poncet and Professor Zenios.

## 1.8 Appendix

Table 1.1: This table reports the linear correlation coefficient between economic policy and institutional effectiveness, and between economic policy and each of the three sub-components of institutional effectiveness: political instability, corruption, and legal and administrative restrictions. The table reports the **correlation *over time***, which is computed as the cross-sectional average of the correlation over time of the two variables for each country. As to the correlation in differences, we proceed as follows. Denoting with $X$ and $Y$ the two variables for which we aim to study the correlation, we first compute the series of the time differences $X_t^* = X_t - X_{t-1}$ and $Y_t^* = Y_t - Y_{t-1}$, and we then compute the correlation on the series $X^*$ and $Y^*$. The sample covers 42 countries worldwide, divided into 22 developed countries and 20 emerging markets, according to the MSCI classification. The sample period covers 25 years, from 1992 to 2016. Data are at semi-annual frequency, apart from corruption, for which the frequency is annual. Data for institutional effectiveness come from The Economist Intelligence Unit (EIU), data for policy, instability, and legal and administrative restrictions are provided by the IFO Research Center. Data regarding corruption are available from Transparency International.

| | ***Correlation in levels*** | | | ***Correlation in differences*** | | |
|---|---|---|---|---|---|---|
| | **Developed** | **Emerging** | **All** | **Developed** | **Emerging** | **All** |
| **Policy - Institutions** | 0.101 | -0.065 | 0.020 | 0.062 | -0.070 | -0.002 |

| | ***Correlation in levels*** | | | ***Correlation in differences*** | | |
|---|---|---|---|---|---|---|
| | **Developed** | **Emerging** | **All** | **Developed** | **Emerging** | **All** |
| **Policy - Political instability** | -0.391 | -0.452 | -0.420 | -0.137 | -0.102 | -0.120 |
| **Policy - Corruption** | -0.155 | -0.148 | -0.152 | -0.130 | -0.063 | -0.098 |
| **Policy - Restrictions** | -0.217 | -0.131 | -0.176 | 0.024 | -0.049 | -0.010 |

Table 1.2: This table reports the linear correlation coefficient between economic policy and institutional effectiveness, and between economic policy and each of the three sub-components of institutional effectiveness: political instability, corruption, and legal and administrative restrictions. The table reports the **correlation *across countries***, which is computed as the time average of the cross-sectional correlation of the two variables for each time $t$. As to the correlation in differences, we proceed as follows. Denoting with $X$ and $Y$ the two variables for which we wim to study the correlation, we first compute the series of the time differences $X_t^* = X_t - X_{t-1}$ and $Y_t^* = Y_t - Y_{t-1}$, and we then compute the correlation on the series $X^*$ and $Y^*$. The sample covers 42 countries worldwide, divided into 22 developed countries and 20 emerging markets, according to the MSCI classification. The sample period covers 25 years, from 1992 to 2016. Data are at semi-annual frequency, apart from corruption, for which the frequency is annual. Data for institutional effectiveness come from The Economist Intelligence Unit (EIU), data for policy, instability, and legal and administrative restrictions are provided by the IFO Research Center. Data regarding corruption are available from Transparency International.

| | ***Correlation in levels*** | | | ***Correlation in differences*** | | |
|---|---|---|---|---|---|---|
| | **Developed** | **Emerging** | **All** | **Developed** | **Emerging** | **All** |
| **Policy - Institutions** | 0.525 | 0.114 | -0.107 | 0.089 | -0.043 | -0.021 |

| | ***Correlation in levels*** | | | ***Correlation in differences*** | | |
|---|---|---|---|---|---|---|
| | **Developed** | **Emerging** | **All** | **Developed** | **Emerging** | **All** |
| **Policy - Political instability** | -0.484 | -0.478 | -0.542 | -0.087 | -0.085 | -0.095 |
| **Policy - Corruption** | -0.145 | -0.149 | -0.152 | -0.131 | -0.063 | -0.098 |
| **Policy - Restrictions** | -0.230 | -0.157 | -0.313 | 0.033 | -0.067 | -0.016 |

Table 1.3: We present the dynamics of quarterly CDS spreads (in basis points) of the five groups of countries sorted according to our four political variables. Data are quarterly and cover the period 2008-2016. At each quarter, we classify the countries in five groups according to their scores for each of these variables. We then compute the average of the CDS spreads of all the countries assigned to each group. We rebalance the groups every six months for the variables economic policy, political instability, and legal and administrative restrictions, since data are at semi-annual frequency. Regarding corruption, we rebalance the groups every year given that data at annual frequency. To conclude, we compute the average over time of the CDS spreads of each group, which are the numbers reported in this table. Results are presented monotonically from the best group (best policies, highest stability, lowest level of corruption and restrictions) to the worst one.

**Developed countries**

| | *Top 20* | *Group 2* | *Group 3* | *Group 4* | *Worst 20* |
|---|---|---|---|---|---|
| **Policy** | 53.95 | 63.34 | 60.79 | 127.94 | 376.58 |
| **Stability** | 47.04 | 58.14 | 92.76 | 106.03 | 424.20 |
| **Corruption** | 64.54 | 31.30 | 48.25 | 79.38 | 467.87 |
| **Restrictions** | 72.25 | 77.75 | 70.90 | 110.32 | 380.86 |

**Emerging markets**

| | *Top 20* | *Group 2* | *Group 3* | *Group 4* | *Worst 20* |
|---|---|---|---|---|---|
| **Policy** | 119.28 | 133.55 | 140.87 | 157.67 | 182.09 |
| **Stability** | 118.25 | 139.63 | 160.96 | 151.61 | 167.58 |
| **Corruption** | 109.39 | 160.57 | 175.33 | 123.31 | 169.25 |
| **Restrictions** | 138.87 | 142.63 | 127.81 | 165.62 | 158.07 |

**All countries**

| | *Top 20* | *Group 2* | *Group 3* | *Group 4* | *Worst 20* |
|---|---|---|---|---|---|
| **Policy** | 70.58 | 93.03 | 108.28 | 189.96 | 242.78 |
| **Stability** | 56.02 | 104.30 | 121.64 | 145.63 | 305.64 |
| **Corruption** | 48.44 | 64.36 | 129.96 | 246.02 | 228.78 |
| **Restrictions** | 82.82 | 103.31 | 126.72 | 149.40 | 261.05 |

Table 1.4: We test here the statistical and economic difference between the average CDS spread of the countries that belong to the first quintile for their policy (first block of the table) and for their stability (second block), and the average CDS spread of the countries falling in the last and worst quintile. At each quarter, we have an average CDS spread for the countries in the first quintiles, and one for those in the last quintile. We then compute the time-series average of these spreads for both quintiles in the period 2008-2016. We present the difference between the time average of the CDS spreads for the best and worst quintiles. Below, we also test if the time-series of CDS spreads of the best and worst group have a statistically different mean.

**Top 20% - Worst 20% Policy**

| | **Developed** | **Emerging** | **All** |
|---|---|---|---|
| *Difference* | 322.62 | 62.81 | 172.20 |
| *t-Stat* | 9.26*** | 17.77*** | 11.01*** |
| *p-value* | 0.00000 | 0.00000 | 0.00000 |

**Top 20% - Worst 20% Stability**

| | **Developed** | **Emerging** | **All** |
|---|---|---|---|
| *Difference* | 377.16 | 49.34 | 249.62 |
| *t-Stat* | 10.90*** | 5.18*** | 8.59*** |
| *p-value* | 0.00000 | 0.00000 | 0.00000 |

Table 1.5: We test here the statistical and economic difference between the average CDS spread of the countries that belong to the first quintile for their corruption (first block of the table) and for their legal and administrative restrictions (second block), and the average CDS spread of the countries falling in the last and worst quintile. At each quarter, we have an average CDS spread for the countries in the first quintiles, and one for those in the last quintile. We then compute the time-series average of these spreads for both quintiles in the period 2008-2016. We present the difference between the time average of the CDS spreads for the best and worst quintiles. Below, we also test if the time-series of CDS spreads of the best and worst group have a statistically different mean.

**Top 20% - Worst 20% Corruption**

| | **Developed** | **Emerging** | **All** |
|---|---|---|---|
| *Difference* | 403.32 | 59.86 | 180.34 |
| *t-Stat* | 12.83*** | 7.90*** | 13.75*** |
| *p-value* | 0.00000 | 0.00000 | 0.00000 |

**Top 20% - Worst 20% Restrictions**

| | **Developed** | **Emerging** | **All** |
|---|---|---|---|
| *Difference* | 308.61 | 19.20 | 178.23 |
| *t-Stat* | 8.46*** | 3.28*** | 8.43*** |
| *p-value* | 0.00000 | 0.00115 | 0.00000 |

Table 1.6: This table presents the average quarterly CDS spreads (in basis points) for the bivariate sort based on economic policy and political instability. "Strategy 20-80" means that we divide our countries in quintiles, from the best policies to the worst ones. We do the same for political instability. At each quarter, we then select those countries belonging, at the same time, to the group "Top 20%" for policy and for stability, *i.e.* those countries with good policy and high political stability. We compute, at every quarter, the cross-sectional average of the CDS spreads of the countries falling into this group. We report in this table the time average of the quarterly average CDS spread for that group. We do the same for the group of countries being the worst 20% for policy and stability (last quintile), i.e. those countries with worst policies and highest political instability. We then complete the matrix accordingly. Data refer to the period 2008-2016.

**STRATEGY 20-80**

**Developed countries**

| | *Worst stability* | *Top stability* |
|---|---|---|
| *Top policy* | 74.15 | 30.41 |
| *Worst policy* | 568.86 | 57.00 |

**Emerging markets**

| | *Worst stability* | *Top stability* |
|---|---|---|
| *Top policy* | 112.54 | 105.69 |
| *Worst policy* | 187.10 | 173.51 |

**All countries together**

| | *Worst stability* | *Top stability* |
|---|---|---|
| *Top policy* | 154.47 | 57.72 |
| *Worst policy* | 406.71 | 70.43 |

Table 1.7: This table presents the average quarterly CDS spreads (in basis points) for the bivariate sort based on economic policy and political instability. "Strategy 33-66" means that we divide our countries in three groups: those with good policy, ugly policy and bad policy. We do the same for political instability. At each quarter, we then select those countries belonging, at the same time, to the group "Top 33%" for policy and for stability, *i.e.* those countries with good policy and high political stability. We compute, at every quarter, the cross-sectional average of the CDS spreads of the countries falling into this group. We report in this table the time average of the quarterly average CDS spread for that group. We do the same for the group of countries being the worst 33% for policy and stability, i.e. those countries with worst policies and highest political instability. We then complete the matrix accordingly. Data refer to the period 2008-2016.

**STRATEGY 33-66**

**Developed countries**

| | *Worst stability* | *Top stability* |
|---|---|---|
| *Top policy* | 88.02 | 39.18 |
| *Worst policy* | 384.22 | 78.25 |

**Emerging markets**

| | *Worst stability* | *Top stability* |
|---|---|---|
| *Top policy* | 111.13 | 119.63 |
| *Worst policy* | 181.13 | 147.08 |

**All countries together**

| | *Worst stability* | *Top stability* |
|---|---|---|
| *Top policy* | 151.69 | 65.26 |
| *Worst policy* | 312.14 | 96.25 |

Table 1.8: This table presents the results of the regressions of quarterly CDS spreads (in basis points) on our political target variables (economic policy and political instability) and the control macroeconomic variables (GDP growth rate, unemployment rate, primar balance over the GDP, total debt over the GDP, and the slope of the term structure computed as long-term bonds minus short-term rates). In order to fully disentangle the effect of political instability, we first regress political instability on economic policy. We then save the residuals of this regression, which can be interpreted as the part of political instability that is orthogonal to economic policy, *i.e.* the level of political instability that is not due to shocks to the economic policy. The sample comprises **37 countries (developed and emerging together)** in the period 2008-2016. The description of all variables is provided in Section 3. All model specifications are robust to country fixed-effects. Standard errors are robust (Huber-White sandwich estimator). In order to deal with the small sample, we always boostrap the standard errors with 5,000 replications for each model specification.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | 0.841*** | | 1.193*** | | 0.517*** |
| | (3.87) | | (4.76) | | (3.10) |
| Stability residual | | -30.113*** | -34.349*** | | -19.234*** |
| | | (-4.75) | (-5.07) | | (-5.53) |
| GDP | | | | -6.126 | -3.979 |
| | | | | (-0.20) | (-0.12) |
| Unemployment | | | | 53.383*** | 52.560*** |
| | | | | (10.21) | (10.50) |
| Balance | | | | 8.462*** | 7.831*** |
| | | | | (3.99) | (3.69) |
| Debt | | | | -0.726 | -1.221** |
| | | | | (-1.29) | (-2.08) |
| Term slope | | | | 22.256*** | 22.804*** |
| | | | | (5.56) | (5.87) |
| Constant | 91.792*** | 145.693*** | 67.740*** | -260.429*** | -255.600*** |
| | (5.99) | (20.40) | (4.06) | (-5.22) | (-5.08) |
| N | 1268 | 1268 | 1268 | 1119 | 1119 |
| R-Squared | 0.011 | 0.039 | 0.059 | 0.551 | 0.565 |

Table 1.9: This table presents the results of the regressions of quarterly CDS spreads (in basis points) on our political target variables (economic policy and political instability) and the control macroeconomic variables (GDP growth rate, unemployment rate, primar balance over the GDP, total debt over the GDP, and the slope of the term structure computed as long-term bonds minus short-term rates). In order to fully disentangle the effect of political instability, we first regress political instability on economic policy. We then save the residuals of this regression, which can be interpreted as the part of political instability that is orthogonal to economic policy, *i.e.* the level of political instability that is not due to shocks to the economic policy. The sample comprises **17 emerging markets** in the period 2008-2016. The description of all variables is provided in Section 3. All model specifications are robust to country fixed-effects. Standard errors are robust (Huber-White sandwich estimator). In order to deal with the small sample, we always boostrap the standard errors with $5,000$ replications for each model specification.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | 0.639*** | | 0.676*** | | 0.523*** |
| | (4.49) | | (4.70) | | (3.33) |
| Stability residual | | -11.639*** | -12.490*** | | -14.927*** |
| | | (-3.05) | (-3.32) | | (-3.83) |
| GDP | | | | -14.048 | -9.763 |
| | | | | (-0.69) | (-0.45) |
| Unemployment | | | | 19.865*** | 21.652*** |
| | | | | (5.12) | (5.69) |
| Balance | | | | -13.765*** | -12.799*** |
| | | | | (-3.39) | (-3.12) |
| Debt | | | | 1.193 | 0.042 |
| | | | | (1.34) | (0.05) |
| Term slope | | | | -5.693** | -4.878* |
| | | | | (-2.05) | (-1.79) |
| Constant | 105.625*** | 149.254*** | 103.073*** | -54.053 | -54.813 |
| | (10.67) | (41.46) | (10.09) | (-1.21) | (-1.28) |
| N | 595 | 595 | 595 | 453 | 453 |
| R-Squared | 0.027 | 0.021 | 0.051 | 0.225 | 0.265 |

Table 1.10: This table presents the results of the regressions of quarterly CDS spreads (in basis points) on our political target variables (economic policy and political instability) and the control macroeconomic variables (GDP growth rate, unemployment rate, primar balance over the GDP, total debt over the GDP, and the slope of the term structure computed as long-term bonds minus short-term rates). In order to fully disentangle the effect of political instability, we first regress political instability on economic policy. We then save the residuals of this regression, which can be interpreted as the part of political instability that is orthogonal to economic policy, *i.e.* the level of political instability that is not due to shocks to the economic policy. The sample comprises **20 developed countries** in the period 2008-2016. The description of all variables is provided in Section 3. All model specifications are robust to country fixed-effects. Standard errors are robust (Huber-White sandwich estimator). In order to deal with the small sample, we always boostrap the standard errors with $5,000$ replications for each model specification.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | 1.021*** | | 1.589*** | | 4.223*** |
| | (2.59) | | (3.48) | | (8.72) |
| Stability residual | | -44.088*** | -49.661*** | | -18.576*** |
| | | (-4.24) | (-4.50) | | (-3.97) |
| GDP | | | | -163.061 | -223.096 |
| | | | | (-0.67) | (-0.95) |
| Unemployment | | | | 58.018*** | |
| | | | | (9.69) | |
| Balance | | | | 11.751*** | 10.419*** |
| | | | | (5.04) | (4.42) |
| Debt | | | | -1.712*** | -2.012*** |
| | | | | (-2.60) | (-2.98) |
| Term slope | | | | 28.520*** | 29.017*** |
| | | | | (5.06) | (5.21) |
| Unemployment res | | | | | 56.981*** |
| | | | | | (9.33) |
| Constant | 80.535*** | 142.532*** | 42.900 | -246.674*** | -10.918 |
| | (2.99) | (11.27) | (1.46) | (-4.15) | (-0.20) |
| N | 673 | 673 | 673 | 666 | 666 |
| R-Squared | 0.009 | 0.056 | 0.077 | 0.636 | 0.643 |

Table 1.11: We present the dynamics of annual depreciation/appreciation rate of the local currency with respect to the US dollar of the five groups of countries sorted according to our four political variables. Data cover the period 1992-2016. At each quarter, we classify the countries in five groups according to their scores for each of these variables. We then compute the average of the depreciation/appreciation rate of all the currencies of the countries assigned to each group. We rebalance the groups every six months for the variables economic policy and political instability, since data are at semi-annual frequency. To conclude, we compute the average over time of the depreciation/appreciation rate of each group, which are the numbers reported in this table. Results are presented monotonically from the best group (best policies, highest stability, lowest level of corruption and restrictions) to the worst one. The "minus" refers to a depreciation with respect to the US dollar, the "plus" to an appreciation.

**Developed countries**

| | *Top 20* | *Group 2* | *Group 3* | *Group 4* | *Worst 20* |
|---|---|---|---|---|---|
| **Policy** | 0.59% | −0.82% | 1.45% | 0.00% | −2.85% |
| **Stability** | −0.50% | −0.82% | 1.15% | 0.22% | −2.64% |

**Emerging markets**

| | *Top 20* | *Group 2* | *Group 3* | *Group 4* | *Worst 20* |
|---|---|---|---|---|---|
| **Policy** | −2.78% | −5.19% | −2.61% | −10.11% | −14.21% |
| **Stability** | −2.40% | −3.30% | −5.39% | −6.86% | −22.93% |

**All countries**

| | *Top 20* | *Group 2* | *Group 3* | *Group 4* | *Worst 20* |
|---|---|---|---|---|---|
| **Policy** | −1.02% | −1.75% | −3.50% | −8.37% | −12.94% |
| **Stability** | −0.72% | −1.16% | −2.73% | −6.06% | −17.62% |

Table 1.12: This table presents the alphas of a long-short strategy that buys the currencies of those countries in the top 20% for economic policy, political stability and the intersection of the latter two groups, and that short-sells the currencies belonging to the worst 20% group. Our sample comprises 30 countries in the period 1992-2016. We test several models: "CAPM" refers to the international capital asset pricing model, "FF 3" and "FF 5" to the three-factor and five-factor Fama-French models, "Carhart" to the three-factor Fama-French model plus the momentum factor, "6 F" to the six-factor asset pricing model including all the factors in the Carhart and five-factor Fama-French model, "RX" and "HML" to the carry trade risk factors of Lustig et al. (2011), "ALL 9" to all the aforementioned factors together. Alphas are annualized.

**UNIVARIATE SORT ON ECONOMIC POLICY**

| | **CAPM** | **FF 3** | **Carhart** | **FF 5** | **6 F** | **RX** | **HML** | **RX-HML** | **ALL 9** |
|---|---|---|---|---|---|---|---|---|---|
| *Alpha* | 8.26% | 8.20% | 8.40% | 9.59% | 9.54% | 9.71% | 11.38% | 11.42% | 12.47% |
| *t-Stat* | 3.18*** | 3.01*** | 2.85*** | 3.11*** | 2.99*** | 3.48*** | 3.90*** | 3.89*** | 3.63*** |
| *p-value* | 0.00196 | 0.00331 | 0.00531 | 0.00248 | 0.00356 | 0.00077 | 0.00018 | 0.00019 | 0.00048 |

**UNIVARIATE SORT ON POLITICAL INSTABILITY**

| | **CAPM** | **FF 3** | **Carhart** | **FF 5** | **6 F** | **RX** | **HML** | **RX-HML** | **ALL 9** |
|---|---|---|---|---|---|---|---|---|---|
| *Alpha* | 13.46% | 14.06% | 14.62% | 15.55% | 15.74% | 14.82% | 18.68% | 18,45% | 20,43% |
| *t-Stat* | 3.31*** | 3.30*** | 3.18*** | 3.22*** | 3.15*** | 3.50*** | 4.26*** | 4.20*** | 3.85*** |
| *p-value* | 0.00132 | 0.00135 | 0.00201 | 0.00178 | 0.00221 | 0.00072 | 0.00000 | 0.00000 | 0.00023 |

**BIVARIATE SORT ON POLICY AND INSTABILITY**

| | **CAPM** | **FF 3** | **Carhart** | **FF 5** | **6 F** | **RX** | **HML** | **RX-HML** | **ALL 9** |
|---|---|---|---|---|---|---|---|---|---|
| *Alpha* | 23.25% | 22.93% | 22.23% | 27.82% | 26.64% | 26.40% | 32.31% | 32.66% | 36.33% |
| *t-Stat* | 3.28*** | 3.08*** | 2.77*** | 3.31*** | 3.08*** | 3.53*** | 4.18*** | 4.21*** | 3.97*** |
| *p-value* | 0.00145 | 0.00266 | 0.00683 | 0.00130 | 0.00274 | 0.0006 | 0.00000 | 0.00000 | 0.00015 |

Table 1.13: This table presents the results of the regressions of quarterly depreciation rates of the currencies in our sample against the US dollar, on our political target variables (economic policy and political instability) and the control macroeconomic variables (GDP growth rate, unemployment rate, primar balance over the GDP, total debt over the GDP, and the slope of the term structure computed as long-term bonds minus short-term rates). In order to fully disentangle the effect of political instability, we first regress political isntability on economic policy. We then save the residuals of this regression, which can be interpreted as the part of political instability that is orthogonal to economic policy, *i.e.* the level of political instability that is not due to shocks to the economic policy. The sample comprises **30 countries** in the period 1992-2016. The description of all variables is provided in Section 3. All model specifications are robust to country fixed-effects. Standard errors are robust (Huber-White sandwich estimator). In order to deal with the small sample, we always boostrap the standard errors with 5,000 replications for each model specification.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | 0.000*** | | 0.001*** | | 0.000*** | 0.000*** |
| | (5.24) | | (5.19) | | (4.55) | (3.70) |
| Stability res | | -0.006*** | -0.008*** | | -0.002* | -0.001 |
| | | (-2.97) | (-3.57) | | (-1.74) | (-0.63) |
| GDP | | | | -0.102* | -0.073 | -0.092* |
| | | | | (-1.91) | (-1.41) | (-1.70) |
| Unemployment | | | | -0.000 | -0.001 | -0.001 |
| | | | | (-0.23) | (-1.35) | (-0.54) |
| Balance | | | | -0.001 | -0.001 | -0.000 |
| | | | | (-1.19) | (-1.38) | (-0.76) |
| Debt | | | | 0.000** | 0.000 | 0.000* |
| | | | | (2.17) | (1.39) | (1.82) |
| Term slope | | | | -0.000 | | -0.000 |
| | | | | (-0.10) | | (-0.13) |
| Short-term rates | | | | | 0.001*** | |
| | | | | | (2.65) | |
| Constant | -0.016*** | 0.013*** | -0.022*** | -0.002 | -0.012* | -0.014* |
| | (-3.57) | (6.40) | (-3.99) | (-0.26) | (-1.81) | (-1.74) |
| N | 2894 | 2580 | 2580 | 2028 | 2371 | 1905 |
| R-Squared | 0.012 | 0.006 | 0.023 | 0.007 | 0.051 | 0.015 |

Table 1.14: This table reports the annualized returns of the portfolios sorted according to our four political variables. Data cover the period 1992-2016 for policy, stability and restrictions, and 1996-2016 for corruption. Our sample includes the 22 developed markets included in the MSCI classification. All returns are expressed in US dollars. All five portfolios are constructed as an equal average of the countries falling in that particular quintile. We rebalance our portfolios semi-annually for policy, stability and restrictions, and annually for corruption.

| | ***Worst 20%*** | ***Group 2*** | ***Group 3*** | ***Group 4*** | ***Top 20%*** |
|---|---|---|---|---|---|
| **Policy** | -0.36% | 3.80% | 5.87% | 6.55% | 8.76% |
| **Stability** | -0.51% | 5.03% | 6.99% | 3.90% | 7.80% |
| **Restrictions** | 3.06% | 3.46% | 4.96% | 5.63% | 6.73% |
| **Corruption** | -0.81% | 3.44% | 5.02% | 5.70% | 8.28% |

Table 1.15: This table shows the difference between the average returns of the best portfolio, which comprises the countries that fall into the quintile with highest quality of the policy (and, respectively, lowest instability, lowest level of restrictions and lowest level of corruption), and the worst portfolio, which includes the conutries falling in the last quintile (worst policy, highest instability, highest level of restrictions, highest level of corruption). Our sample covers 22 developed countries (MSCI classification) in the period 1992-2016 for policy, instability and restrictions, and 1996-2016 for corruption. The first line reports the difference between the annualized returns of the two portfolios, best minus worst. The second and third line show the t-Stat and the p-value of the test the time-series of quarterly returns of the best portfolios have a different mean than the time-series of the worst portfolio.

| | **Policy** | **Stability** | **Restrictions** | **Corruption** |
|---|---|---|---|---|
| *Difference* | 9.11% | 8.31% | 3.67% | 9.09% |
| *t-Stat* | 4.13*** | 3.41*** | 1.92* | 2.98*** |
| *p-value* | 0.0000 | 0.00046 | 0.02836 | 0.00184 |

Table 1.16: This table shows the abnormal returns generated by the two univariate sorts and the bivariate sort according to our policy and stability indicators. We create long-short portfolios buying the countries in the best quintiles and short-selling those in the worst quintile. Portfolios are formed on the publication date of these political ratings and are rebalanced semi-annually. Alphas are annualized. The sample covers monthly returns for 22 developed markets in the period 1992-2016. The six asset pricing models tested are described in Section 5: we test our strategy returns against the World CAPM, the international Fama-French 3- and 5-factor models, the international Carhart model, the International CAPM of Adler-Dumas and the CAPM Redux. Standard errors are Newey-West.

| **DEVELOPED MARKETS** | **ANNUALIZED ALPHAS** | | | | | | |
|---|---|---|---|---|---|---|---|
| **STRATEGY / MODEL** | **World CAPM** | **Intl FF3** | **Intl Carhart** | **Intl FF5** | **Adler-Dumas** | **CAPM Redux** | |
| **Univariate sort** | | | | | | | |
| **Top 20% - bottom 20% policy** | 5,27% | 6,19% | 6,30% | 5,48% | 5,47% | 5,16% | *Alpha* |
| | 2,57 | 3,57 | 3,65 | 2,85 | 2,59 | 2,54 | *t-Stat* |
| | 0.010 | 0.000 | 0.000 | 0.004 | 0.010 | 0.011 | *p-value* |
| | *** | *** | *** | *** | *** | ** | *Significance* |
| **Top 20% - bottom 20% stability** | 2,69% | 3,40% | 3,49% | 2,97% | 2,84% | 2,65% | *Alpha* |
| | 1,74 | 2,39 | 2,40 | 2,50 | 2,06 | 1,71 | *t-Stat* |
| | 0.084 | 0.017 | 0.017 | 0.013 | 0.041 | 0.088 | *p-value* |
| | * | ** | ** | ** | ** | * | *Significance* |
| **Bivariate sort** | | | | | | | |
| **Top 20% policy & stability** | 9,02% | 10,36% | 9,83% | 9,56% | 9,27% | 8,98% | *Alpha* |
| **- bottom 20% policy & stability** | 2,56 | 3,10 | 2,86 | 2,87 | 2,66 | 2,46 | *t-Stat* |
| | 0.010 | 0.002 | 0.004 | 0.004 | 0.008 | 0.014 | *p-value* |
| | *** | *** | *** | *** | *** | ** | *Significance* |

Table 1.17: This table shows the abnormal returns generated by the two univariate sorts and the bivariate sort according to our policy and stability indicators. We create long-short portfolios buying the countries in the best quintiles and short-selling those in the worst quintile. Portfolios are formed on the publication date of these political ratings and are rebalanced semi-annually. Alphas are annualized. The sample covers monthly returns for 42 countries (22 developed and 20 emerging markets) in the period 1992-2016. The six asset pricing models tested are described in Section 5: we test our strategy returns against the World CAPM, the international Fama-French 3- and 5-factor models, the international Carhart model, the International CAPM of Adler-Dumas and the CAPM Redux. Standard errors are Newey-West.

| **ALL MARKETS** | **ANNUALIZED ALPHAS** | | | | | | |
|---|---|---|---|---|---|---|---|
| **STRATEGY / MODEL** | **World CAPM** | **Intl FF3** | **Intl Carhart** | **Intl FF5** | **Adler Dumas** | **CAPM Redux** | |
| **Univariate sort** | | | | | | | |
| **Top 20% - bottom 20% policy** | 0,89% | 1,41% | 1,05% | 0,97% | 1,05% | 1,09% | *Alpha* |
| | 0,60 | 0,91 | 0,52 | 0,66 | 0,53 | 0,73 | *t-Stat* |
| | 0.549 | 0.363 | 0.601 | 0.511 | 0.596 | 0.468 | *p-value* |
| | | | | | | | *Significance* |
| **Top 20% - bottom 20% stability** | -0,33% | -0,03% | 0,48% | 0,28% | -0,15% | -0,03% | *Alpha* |
| | -0,12 | -0,01 | 0,18 | 0,10 | -0,06 | -0,01 | *t-Stat* |
| | 0.903 | 0.991 | 0.855 | 0.920 | 0.956 | 0.992 | *p-value* |
| | | | | | | | *Significance* |
| **Bivariate sort** | | | | | | | |
| **Top 20% policy & stability** | 4,71% | 5,39% | 5,37% | 5,06% | 4,75% | 5,15% | *Alpha* |
| **- bottom 20% policy & stability** | 2,09 | 2,33 | 2,20 | 1,87 | 1,66 | 2,15 | *t-Stat* |
| | 0.037 | 0.020 | 0.028 | 0.061 | 0.098 | 0.032 | *p-value* |
| | ** | ** | ** | * | * | ** | *Significance* |

Table 1.18: This table reports the results of the panel regressions of quarterly **expected returns** on our political indicators plus the control variables. Our political ratings become available at the publication date. We then compute the returns of each country's stock market starting from the day following the publication date and for all the next quarter. In this way, we make sure that we explain expected returns out of sample. For the sake of consistency, the control variables are also lagged and refer to the previous quarter with respect to expected returns. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **22 developed markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00008 | | -0.00020* | | -0.00025** |
| | (-0.81) | | (-1.79) | | (-2.17) |
| Currency res | -0.32489*** | -0.33533*** | -0.34837*** | -0.33728*** | -0.36522*** |
| | (-5.68) | (-5.95) | (-6.18) | (-6.29) | (-6.73) |
| Stability res | | 0.00530** | 0.00677*** | | 0.00751*** |
| | | (2.47) | (2.74) | | (3.12) |
| GDP | | | | 1.07993*** | 1.07180*** |
| | | | | (4.51) | (4.65) |
| Unemploymentl | | | | 0.00053 | 0.00147 |
| | | | | (0.32) | (0.87) |
| Balance | | | | -0.00180* | -0.00195* |
| | | | | (-1.81) | (-1.94) |
| Debt | | | | -0.00012 | -0.00001 |
| | | | | (-0.80) | (-0.06) |
| Slope | | | | 0.00051 | 0.00055 |
| | | | | (0.21) | (0.23) |
| Constant | 0.03289*** | 0.02459*** | 0.03404*** | 0.02518** | 0.01771 |
| | (5.62) | (8.26) | (5.74) | (2.08) | (1.36) |
| N | 1893 | 1893 | 1893 | 1772 | 1772.00000 |
| R-Squared | 0.02112 | 0.02446 | 0.02635 | 0.04055 | 0.04627 |

Table 1.19: This table reports the results of the panel regressions of quarterly **expected returns** on our political indicators plus the control variables. Our political ratings become available at the publication date. We then compute the returns of each country's stock market starting from the day following the publication date and for all the next quarter. In this way, we make sure that we explain expected returns out of sample. For the sake of consistency, the control variables are also lagged and refer to the previous quarter with respect to expected returns. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **22 developed markets** in the period 1992-2016. We control for **country and time fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00018** | | -0.00030*** | | -0.00024*** |
| | (-2.55) | | (-3.52) | | (-3.01) |
| Currency res | -0.18526*** | -0.19974*** | -0.24344*** | -0.22797*** | -0.27741*** |
| | (-2.99) | (-3.17) | (-3.79) | (-4.16) | (-4.74) |
| Stability res | | 0.00274 | 0.00551*** | | 0.00452*** |
| | | (1.64) | (2.78) | | (2.76) |
| GDP | | | | 0.65158*** | 0.64487*** |
| | | | | (4.49) | (4.53) |
| Unemployment | | | | -0.00044 | 0.00012 |
| | | | | (-0.35) | (0.10) |
| Balance | | | | 0.00080 | 0.00066 |
| | | | | (1.04) | (0.88) |
| Debt | | | | 0.00018 | 0.00022 |
| | | | | (1.33) | (1.59) |
| Slope | | | | -0.00187 | -0.00156 |
| | | | | (-0.90) | (-0.74) |
| Constant | 0.00647 | -0.00545 | 0.00949 | -0.01473 | -0.01305 |
| | (0.54) | (-0.52) | (0.77) | (-0.89) | (-0.77) |
| N | 1893 | 1893 | 1893 | 1772 | 1772 |
| R-Squared | 0.60185 | 0.60118 | 0.60454 | 0.64350 | 0.64597 |

Table 1.20: This table reports the results of the panel regressions of quarterly **expected returns** on our political indicators plus the control variables. Our political ratings become available at the publication date. We then compute the returns of each country's stock market starting from the day following the publication date and for all the next quarter. In this way, we make sure that we explain expected returns out of sample. For the sake of consistency, the control variables are also lagged and refer to the previous quarter with respect to expected returns. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | 0.00000 | | -0.00004 | | -0.00019* |
| | (0.01) | | (-0.38) | | (-1.77) |
| Currency res | -0.47612*** | -0.47985*** | -0.48059*** | -0.48970*** | -0.50378*** |
| | (-9.95) | (-9.86) | (-9.84) | (-9.79) | (-9.88) |
| Stability res | | 0.00306 | 0.00322 | | 0.00536** |
| | | (1.51) | (1.53) | | (2.41) |
| GDP | | | | 0.43684*** | 0.42328*** |
| | | | | (4.38) | (4.25) |
| Unemployment | | | | 0.00147 | 0.00207 |
| | | | | (1.03) | (1.43) |
| Balance | | | | -0.00128 | -0.00148 |
| | | | | (-1.34) | (-1.54) |
| Debt | | | | -0.00017 | -0.00008 |
| | | | | (-1.13) | (-0.49) |
| Slope | | | | 0.00324** | 0.00330** |
| | | | | (2.39) | (2.43) |
| Constant | 0.02733*** | 0.02725*** | 0.02947*** | 0.01612 | 0.01570 |
| | (4.49) | (12.07) | (4.71) | (1.47) | (1.33) |
| N | 3566 | 3566 | 3566 | 2855 | 2855 |
| R-Squared | 0.04706 | 0.04778 | 0.04781 | 0.07295 | 0.07522 |

Table 1.21: This table reports the results of the panel regressions of quarterly **expected returns** on our political indicators plus the control variables. Our political ratings become available at the publication date. We then compute the returns of each country's stock market starting from the day following the publication date and for all the next quarter. In this way, we make sure that we explain expected returns out of sample. For the sake of consistency, the control variables are also lagged and refer to the previous quarter with respect to expected returns. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00002 | | -0.00003 | | -0.00010 |
| | (-0.25) | | (-0.38) | | (-1.24) |
| Currency res | -0.30740*** | -0.30869*** | -0.30945*** | -0.33035*** | -0.34209*** |
| | (-6.75) | (-6.68) | (-6.71) | (-6.07) | (-5.96) |
| Stability res | | 0.00069 | 0.00083 | | 0.00245 |
| | | (0.42) | (0.48) | | (1.39) |
| GDP | | | | 0.30381*** | 0.29751*** |
| | | | | (4.51) | (4.32) |
| Unemployment | | | | 0.00056 | 0.00085 |
| | | | | (0.48) | (0.76) |
| Balance | | | | 0.00095 | 0.00082 |
| | | | | (1.03) | (0.93) |
| Debt | | | | 0.00016 | 0.00019 |
| | | | | (1.21) | (1.40) |
| Slope | | | | 0.00226** | 0.00232** |
| | | | | (2.11) | (2.19) |
| Constant | 0.00258 | 0.00150 | 0.00344 | -0.02437* | -0.02300 |
| | (0.13) | (0.07) | (0.17) | (-1.66) | (-1.48) |
| N | 3566 | 3566 | 3566 | 2855 | 2855 |
| R-Squared | 0.50665 | 0.50667 | 0.50669 | 0.57370 | 0.57417 |

Table 1.22: This table reports the results of the panel regressions of quarterly **realized returns** on our political indicators plus the control variables. The dependent variable and the explanatory variables are all contemporaneous. In this way, we make sure that we explain realized returns out of sample. "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **22 developed markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with 5,000 iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* |
| Policy | -0.00036*** | | -0.00029*** | | -0.00023** | -0.00028** |
| | (-3.29) | | (-2.60) | | (-2.02) | (-2.41) |
| Stability | | 0.00700*** | 0.00543** | | 0.00713*** | 0.00949*** |
| | | (3.09) | (2.41) | | (2.86) | (3.80) |
| GDP | | | | 1.37723*** | 1.00361*** | 1.00361*** |
| | | | | (5.00) | (4.10) | (4.07) |
| Unemployment | | | | 0.00402** | 0.00442*** | 0.00442*** |
| | | | | (2.58) | (2.82) | (2.74) |
| Balance | | | | 0.00070 | 0.00039 | 0.00039 |
| | | | | (0.64) | (0.37) | (0.36) |
| Debt | | | | -0.00017 | -0.00007 | -0.00007 |
| | | | | (-1.27) | (-0.48) | (-0.48) |
| Slope | | | | -0.00426 | -0.00428* | -0.00428 |
| | | | | (-1.61) | (-1.65) | (-1.62) |
| Currency | | | | -0.35598*** | -0.35859*** | |
| | | | | (-5.57) | (-5.59) | |
| Currency res | | | | | | -0.35859*** |
| | | | | | | (-5.61) |
| Constant | 0.03766*** | -0.02561* | 0.00045 | -0.00111 | -0.04203* | -0.05639** |
| | (5.57) | (-1.69) | (0.03) | (-0.10) | (-1.68) | (-2.26) |
| N | 2200 | 2158 | 2158 | 1996 | 1956 | 1956 |
| R-Squared | 0.00592 | 0.00521 | 0.00882 | 0.05657 | 0.05460 | 0.05460 |

Table 1.23: This table reports the results of the panel regressions of quarterly **realized returns** on our political indicators plus the control variables. The dependent variable and the explanatory variables are all contemporaneous. In this way, we make sure that we explain realized returns out of sample. "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **22 developed markets** in the period 1992-2016. We control for **country and time fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* |
| Policy | -0.00025*** | | -0.00022*** | | -0.00016** | -0.00019*** |
| | (-3.30) | | (-2.82) | | (-2.27) | (-2.65) |
| Stability | | 0.00475*** | 0.00383** | | 0.00266* | 0.00393** |
| | | (2.85) | (2.30) | | (1.66) | (2.43) |
| GDP | | | | 0.23349* | 0.19465 | 0.19465 |
| | | | | (1.69) | (1.46) | (1.49) |
| Unemployment | | | | 0.00104 | 0.00145 | 0.00145 |
| | | | | (0.95) | (1.31) | (1.31) |
| Balance | | | | 0.00137** | 0.00116* | 0.00116 |
| | | | | (1.97) | (1.67) | (1.63) |
| Debt | | | | 0.00012 | 0.00014 | 0.00014 |
| | | | | (1.00) | (1.11) | (1.12) |
| Slope | | | | -0.00681*** | -0.00659*** | -0.00659*** |
| | | | | (-3.94) | (-3.65) | (-3.84) |
| Currency | | | | -0.18444*** | -0.19243*** | |
| | | | | (-4.01) | (-4.07) | |
| Currency res | | | | | | -0.19243*** |
| | | | | | | (-4.23) |
| Constant | 0.03347** | -0.01473 | 0.00626 | -0.01515 | -0.02462 | -0.03233 |
| | (2.38) | (-0.83) | (0.35) | (-0.59) | (-0.84) | (-1.15) |
| N | 2200 | 2158 | 2158 | 1996 | 1956 | 1956 |
| R-Squared | 0.67024 | 0.66074 | 0.66266 | 0.70380 | 0.69943 | 0.69943 |

Table 1.24: This table reports the results of the panel regressions of quarterly **realized returns** on our political indicators plus the control variables. The dependent variable and the explanatory variables are all contemporaneous. In this way, we make sure that we explain realized returns out of sample.”Stability res” refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, ”Currency res” represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growtth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **22 developed markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with 5,000 iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00029*** | -0.00039*** | -0.00023** | -0.00036*** | -0.00028** | -0.00046*** |
| | (-2.62) | (-3.46) | (-2.00) | (-3.03) | (-2.42) | (-3.89) |
| Stability | 0.00543** | | 0.00713*** | | 0.00949*** | |
| | (2.39) | | (2.85) | | (3.76) | |
| Stability ort | | 0.00543** | | 0.00713* ** | | 0.00949*** |
| | | (2.38) | | (2.86) | | (3.79) |
| GDP | | | 1.00361*** | 1.00361*** | 1.00361*** | 1.00361*** |
| | | | (4.08) | (4.15) | (4.08) | (4.19) |
| Unemployment | | | 0.00442*** | 0.00442*** | 0.00442*** | 0.00442*** |
| | | | (2.77) | (2.75) | (2.74) | (2.83) |
| Balance | | | 0.00039 | 0.00039 | 0.00039 | 0.00039 |
| | | | (0.37) | (0.37) | (0.36) | (0.37) |
| Debt | | | -0.00007 | -0.00007 | -0.00007 | -0.00007 |
| | | | (-0.47) | (-0.47) | (-0.48) | (-0.48) |
| Slope | | | -0.00428 | -0.00428 | -0.00428 | -0.00428 |
| | | | (-1.61) | (-1.62) | (-1.61) | (-1.61) |
| Currency | | | -0.35859*** | -0.35859*** | | |
| | | | (-5.63) | (-5.71) | | |
| Currency res | | | | | -0.35859*** | -0.35859*** |
| | | | | | (-5.63) | (-5.62) |
| Constant | 0.00045 | 0.04242*** | -0.04203* | 0.01303 | -0.05639** | 0.01687 |
| | (0.03) | (6.24) | (-1.69) | (1.07) | (-2.22) | (1.39) |
| N | 2158 | 2158 | 1956 | 1956 | 1956 | 1956 |
| R-Squared | 0.00882 | 0.00882 | 0.05460 | 0.05460 | 0.05460 | 0.05460 |

Table 1.25: This table reports the results of the panel regressions of quarterly **realized returns** on our political indicators plus the control variables. The dependent variable and the explanatory variables are all contemporaneous. In this way, we make sure that we explain realized returns out of sample."Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growtth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **22 developed markets** in the period 1992-2016. We control for **country and time fixed effects**. Standard errors are bootstrapped with 5,000 iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* |
| Policy | -0.00022*** | -0.00029*** | -0.00016** | -0.00021*** | -0.00019*** | -0.00026*** |
| | (-2.83) | (-3.76) | (-2.32) | (-2.98) | (-2.68) | (-3.49) |
| Stability | 0.00383** | | 0.00266* | | 0.00393** | |
| | (2.24) | | (1.67) | | (2.42) | |
| Stability ort | | 0.00383** | | 0.00266* | | 0.00393** |
| | | (2.28) | | (1.68) | | (2.41) |
| GDP | | | 0.19465 | 0.19465 | 0.19465 | 0.19465 |
| | | | (1.41) | (1.45) | (1.43) | (1.44) |
| Unemployment | | | 0.00145 | 0.00145 | 0.00145 | 0.00145 |
| | | | (1.29) | (1.28) | (1.31) | (1.30) |
| Balance | | | 0.00116* | 0.00116* | 0.00116* | 0.00116* |
| | | | (1.65) | (1.67) | (1.74) | (1.71) |
| Debt | | | 0.00014 | 0.00014 | 0.00014 | 0.00014 |
| | | | (1.13) | (1.11) | (1.11) | (1.11) |
| Slope | | | -0.00659*** | -0.00659*** | -0.00659*** | -0.00659*** |
| | | | (-3.76) | (-3.88) | (-3.76) | (-3.93) |
| Currency | | | -0.19243*** | -0.19243*** | | |
| | | | (-4.25) | (-4.19) | | |
| Currency res | | | | | -0.19243*** | -0.19243*** |
| | | | | | (-4.23) | (-4.35) |
| Constant | 0.00626 | 0.03583** | -0.02462 | -0.00407 | -0.03233 | -0.00200 |
| | (0.33) | (2.57) | (-0.84) | (-0.16) | (-1.10) | (-0.08) |
| N | 2158 | 2158 | 1956 | 1956 | 1956 | 1956 |
| R-Squared | 0.66266 | 0.66266 | 0.69943 | 0.69943 | 0.69943 | 0.69943 |

Table 1.26: This table reports the results of the panel regressions of quarterly **realized returns** on our political indicators plus the control variables. The dependent variable and the explanatory variables are all contemporaneous. In this way, we make sure that we explain realized returns out of sample. "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00034*** | | -0.00027** | | -0.00026** | -0.00038*** |
| | (-3.29) | | (-2.50) | | (-2.50) | (-3.64) |
| Stability | | 0.00502** | 0.00353 | | 0.00582*** | 0.01159*** |
| | | (2.38) | (1.58) | | (2.68) | (5.26) |
| GDP | | | | 0.45588*** | 0.38677*** | 0.38677*** |
| | | | | (4.17) | (3.57) | (3.60) |
| Unemployment | | | | 0.00362*** | 0.00384*** | 0.00384*** |
| | | | | (2.62) | (2.79) | (2.82) |
| Balance | | | | 0.00203* | 0.00155 | 0.00155 |
| | | | | (1.95) | (1.45) | (1.46) |
| Debt | | | | -0.00014 | -0.00005 | -0.00005 |
| | | | | (-0.93) | (-0.34) | (-0.34) |
| Slope | | | | 0.00263 | 0.00306 | 0.00306 |
| | | | | (0.91) | (1.03) | (1.04) |
| Currency | | | | -0.87274*** | -0.87676*** | |
| | | | | (-16.10) | (-15.71) | |
| Currency res | | | | | | -0.87676*** |
| | | | | | | (-15.54) |
| Constant | 0.04376*** | -0.00392 | 0.02095 | -0.00226 | -0.02658 | -0.06171*** |
| | (6.69) | (-0.31) | (1.29) | (-0.22) | (-1.23) | (-2.87) |
| N | 4032 | 4038 | 3990 | 3095 | 3047 | 3047 |
| R-Squared | 0.00276 | 0.00179 | 0.00346 | 0.14451 | 0.15159 | 0.15159 |

Table 1.27: This table reports the results of the panel regressions of quarterly **realized returns** on our political indicators plus the control variables. The dependent variable and the explanatory variables are all contemporaneous. In this way, we make sure that we explain realized returns out of sample. "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country and time fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00022*** | | -0.00020** | | -0.00013* | -0.00021*** |
| | (-2.70) | | (-2.48) | | (-1.79) | (-2.86) |
| Stability | | 0.00142 | 0.00060 | | 0.00365** | 0.00727*** |
| | | (0.83) | (0.34) | | (2.23) | (4.32) |
| GDP | | | | 0.24256*** | 0.22913*** | 0.22913*** |
| | | | | (3.21) | (3.01) | (3.04) |
| Unemployment | | | | 0.00039 | 0.00090 | 0.00090 |
| | | | | (0.35) | (0.82) | (0.82) |
| Balance | | | | 0.00148* | 0.00116 | 0.00116 |
| | | | | (1.94) | (1.54) | (1.49) |
| Debt | | | | 0.00023* | 0.00026** | 0.00026** |
| | | | | (1.75) | (2.00) | (2.01) |
| Slope | | | | 0.00112 | 0.00142 | 0.00142 |
| | | | | (0.48) | (0.61) | (0.59) |
| Currency | | | | -0.53834*** | -0.55070*** | |
| | | | | (-11.64) | (-11.83) | |
| Currency res | | | | | | -0.55070*** |
| | | | | | | (-11.72) |
| Constant | 0.06093*** | 0.03837 | 0.05682** | -0.02179 | -0.03886 | -0.06092* |
| | (2.77) | (1.60) | (2.27) | (-0.80) | (-1.26) | (-1.93) |
| N | 4032 | 4038 | 3990 | 3095 | 3047 | 3047 |
| R-Squared | 0.48642 | 0.47931 | 0.47985 | 0.62550 | 0.62256 | 0.62256 |

Table 1.28: This table reports the results of the panel regressions of quarterly **realized returns** on our political indicators plus the control variables. The dependent variable and the explanatory variables are all contemporaneous. In this way, we make sure that we explain realized returns out of sample."Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with 5,000 iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00027** | -0.00037*** | -0.00026** | -0.00044*** | -0.00038*** | -0.00074*** |
| | (-2.51) | (-3.43) | (-2.44) | (-4.08) | (-3.62) | (-6.86) |
| Stability | 0.00353 | | 0.00582*** | | 0.01159*** | |
| | (1.57) | | (2.67) | | (5.33) | |
| Stability ort | | 0.00353 | | 0.00582*** | | 0.01159*** |
| | | (1.58) | | (2.67) | | (5.30) |
| GDP | | | 0.38677*** | 0.38677*** | 0.38677*** | 0.38677*** |
| | | | (3.56) | (3.66) | (3.62) | (3.57) |
| Unemployment | | | 0.00384*** | 0.00384*** | 0.00384*** | 0.00384*** |
| | | | (2.81) | (2.85) | (2.77) | (2.79) |
| Balance | | | 0.00155 | 0.00155 | 0.00155 | 0.00155 |
| | | | (1.44) | (1.42) | (1.42) | (1.42) |
| Debt | | | -0.00005 | -0.00005 | -0.00005 | -0.00005 |
| | | | (-0.34) | (-0.34) | (-0.34) | (-0.34) |
| Slope | | | 0.00306 | 0.00306 | 0.00306 | 0.00306 |
| | | | (1.03) | (1.01) | (1.02) | (1.03) |
| Currency | | | -0.87676*** | -0.87676*** | | |
| | | | (-15.63) | (-15.48) | | |
| Currency res | | | | | -0.87676*** | -0.87676*** |
| | | | | | (-15.74) | (-15.31) |
| Constant | 0.02095 | 0.04792*** | -0.02658 | 0.01783 | -0.06171*** | 0.02669** |
| | (1.26) | (6.92) | (-1.25) | (1.57) | (-2.86) | (2.32) |
| N | 3990 | 3990 | 3047 | 3047 | 3047 | 3047 |
| R-Squared | 0.00346 | 0.00346 | 0.15159 | 0.15159 | 0.15159 | 0.15159 |

Table 1.29: This table reports the results of the panel regressions of quarterly **realized returns** on our political indicators plus the control variables. The dependent variable and the explanatory variables are all contemporaneous. In this way, we make sure that we explain realized returns out of sample."Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **22 developed markets** in the period 1992-2016. We control for **country and time fixed effects**. Standard errors are bootstrapped with 5,000 iterations.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00020** | -0.00022*** | -0.00013* | -0.00025*** | -0.00021*** | -0.00043*** |
| | (-2.49) | (-2.58) | (-1.78) | (-3.04) | (-2.83) | (-5.38) |
| Stability | 0.00060 | | 0.00365** | | 0.00727*** | |
| | (0.34) | | (2.19) | | (4.28) | |
| Stability ort | | 0.00060 | | 0.00365** | | 0.00727*** |
| | | (0.34) | | (2.23) | | (4.38) |
| GDP | | | 0.22913*** | 0.22913*** | 0.22913*** | 0.22913*** |
| | | | (3.10) | (3.02) | (3.10) | (3.10) |
| Unemployment | | | 0.00090 | 0.00090 | 0.00090 | 0.00090 |
| | | | (0.82) | (0.81) | (0.82) | (0.83) |
| Balance | | | 0.00116 | 0.00116 | 0.00116 | 0.00116 |
| | | | (1.51) | (1.50) | (1.49) | (1.49) |
| Debt | | | 0.00026** | 0.00026** | 0.00026** | 0.00026** |
| | | | (2.00) | (2.05) | (2.03) | (1.98) |
| Slope | | | 0.00142 | 0.00142 | 0.00142 | 0.00142 |
| | | | (0.60) | (0.59) | (0.60) | (0.60) |
| Currency | | | -0.55070*** | -0.55070*** | | |
| | | | (-11.86) | (-11.86) | | |
| Currency res | | | | | -0.55070*** | -0.55070*** |
| | | | | | (-11.78) | (-11.68) |
| Constant | 0.05682** | 0.06138*** | -0.03886 | -0.01104 | -0.06092* | -0.00548 |
| | (2.22) | (2.82) | (-1.21) | (-0.39) | (-1.93) | (-0.19) |
| N | 3990 | 3990 | 3047 | 3047 | 3047 | 3047 |
| R-Squared | 0.47985 | 0.47985 | 0.62256 | 0.62256 | 0.62256 | 0.62256 |

Table 1.30: This table reports the results of the panel predictive regressions of future **GDP growth rates** on our political indicators plus the control variables. We run different models with several horizons in our predictive regressions: we start from predicting (out of sample) the 3-month future growth rate until the 5-year future growth rate. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | GDP 3m | GDP 6m | GDP 1y | GDP 2y | GDP 3y | GDP 4y | GDP 5y |
|---|---|---|---|---|---|---|---|
| | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* |
| Policy | -0.00013*** | -0.00018*** | -0.00023*** | -0.00036*** | -0.00042*** | -0.00049*** | -0.00041*** |
| | (-4.72) | (-5.34) | (-8.39) | (-8.45) | (-7.14) | (-6.79) | (-4.60) |
| Stability res | 0.00171*** | 0.00242*** | 0.00272*** | 0.00445*** | 0.00688*** | 0.00806*** | 0.00702*** |
| | (2.82) | (3.57) | (4.95) | (5.12) | (5.75) | (5.65) | (4.10) |
| Unemployment | 0.00097*** | 0.00182*** | 0.00269*** | 0.00633*** | 0.00976*** | 0.01309*** | 0.01593*** |
| | (3.08) | (4.77) | (8.77) | (12.73) | (15.77) | (17.87) | (19.00) |
| Balance | 0.00037** | 0.00052** | 0.00062*** | 0.00133*** | 0.00229*** | 0.00263*** | 0.00158** |
| | (2.07) | (2.57) | (3.39) | (3.96) | (4.95) | (4.92) | (2.36) |
| Debt | -0.00010*** | -0.00015*** | -0.00020*** | -0.00020** | -0.00002 | 0.00015 | 0.00018 |
| | (-3.00) | (-3.45) | (-4.23) | (-2.36) | (-0.22) | (1.31) | (1.34) |
| Slope | 0.00060*** | 0.00060*** | 0.00056*** | 0.00032 | 0.00030 | 0.00046 | 0.00007 |
| | (3.28) | (2.68) | (2.65) | (1.07) | (0.83) | (0.98) | (0.12) |
| Currency res | -0.03502** | -0.02560 | -0.02038 | 0.00975 | -0.01099 | -0.04273* | -0.01202 |
| | (-2.13) | (-1.48) | (-1.52) | (0.66) | (-0.56) | (-1.71) | (-0.40) |
| Constant | 0.02202*** | 0.02886*** | 0.03557*** | 0.04908*** | 0.04940*** | 0.05285*** | 0.06252*** |
| | (8.20) | (8.82) | (11.22) | (7.91) | (6.06) | (5.71) | (6.07) |
| N | 2352 | 2352 | 2352 | 2352 | 2352 | 2352 | 2193 |
| R-Squared | 0.01732 | 0.02311 | 0.06428 | 0.08495 | 0.11208 | 0.13219 | 0.12334 |

Table 1.31: This table reports the results of the panel predictive regressions of future **GDP growth rates** on our political indicators plus the control variables. We run different models with several horizons in our predictive regressions: we start from predicting (out of sample) the 3-month future growth rate until the 5-year future growth rate. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country and time fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | GDP 3m | GDP 6m | GDP 1y | GDP 2y | GDP 3y | GDP 4y | GDP 5y |
|---|---|---|---|---|---|---|---|
| | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* | *β (t-Stat)* |
| Policy | -0.00011*** | -0.00016*** | -0.00022*** | -0.00037*** | -0.00045*** | -0.00051*** | -0.00048*** |
| | (-4.13) | (-4.76) | (-9.58) | (-10.24) | (-8.58) | (-7.58) | (-5.68) |
| Stability res | 0.00164*** | 0.00216*** | 0.00259*** | 0.00398*** | 0.00632*** | 0.00730*** | 0.00763*** |
| | (2.71) | (3.13) | (5.20) | (5.07) | (5.57) | (5.14) | (4.45) |
| Unemployment | -0.00009 | 0.00020 | 0.00065** | 0.00252*** | 0.00506*** | 0.00789*** | 0.00954*** |
| | (-0.25) | (0.52) | (2.51) | (5.99) | (8.75) | (11.31) | (11.33) |
| Balance | 0.00024 | 0.00037 | 0.00043** | 0.00110*** | 0.00156*** | 0.00117** | -0.00105 |
| | (0.95) | (1.34) | (2.29) | (3.23) | (3.35) | (2.05) | (-1.32) |
| Debt | -0.00001 | 0.00001 | 0.00002 | 0.00019** | 0.00053*** | 0.00083*** | 0.00091*** |
| | (-0.22) | (0.13) | (0.52) | (2.48) | (5.14) | (7.14) | (6.79) |
| Slope | 0.00041** | 0.00037* | 0.00027 | 0.00013 | 0.00006 | 0.00023 | 0.00006 |
| | (2.15) | (1.81) | (1.61) | (0.60) | (0.23) | (0.60) | (0.15) |
| Currency res | -0.03574* | -0.01426 | -0.01934 | -0.01660 | -0.04380* | -0.04121 | -0.02580 |
| | (-1.72) | (-0.56) | (-0.98) | (-0.91) | (-1.71) | (-1.26) | (-0.64) |
| Constant | 0.02903*** | 0.03485*** | 0.04014*** | 0.08253*** | 0.08975*** | 0.08841*** | 0.10809*** |
| | (4.17) | (4.84) | (6.19) | (7.58) | (7.23) | (4.50) | (5.47) |
| N | 2352 | 2352 | 2352 | 2352 | 2352 | 2352 | 2193 |
| R-Squared | 0.17275 | 0.22030 | 0.44513 | 0.42663 | 0.38366 | 0.35615 | 0.35247 |

Table 1.32: This table reports the results of the panel predictive regressions of future growth rates of **industrial production** on our political indicators plus the control variables. We run different models with several horizons in our predictive regressions: we start from predicting (out of sample) the 3-month future growth rate until the 5-year future growth rate. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | IP 3m | IP 6m | IP 1y | IP 2y | IP 3y | IP 4y | IP 5y |
|---|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00009*** | -0.00019*** | -0.00029*** | -0.00032*** | -0.00041*** | -0.00046*** | -0.00054*** |
| | (-2.82) | (-4.72) | (-5.69) | (-4.43) | (-4.51) | (-4.33) | (-4.43) |
| Stability res | 0.00109 | 0.00261*** | 0.00503*** | 0.00693*** | 0.00922*** | 0.00959*** | 0.00811*** |
| | (1.59) | (2.83) | (4.57) | (4.58) | (4.78) | (4.43) | (3.38) |
| Currency res | -0.03833*** | -0.06859*** | -0.00821 | 0.04646* | 0.02395 | -0.03644 | 0.04321 |
| | (-2.62) | (-3.93) | (-0.37) | (1.65) | (0.69) | (-0.98) | (1.03) |
| Slope | 0.00041 | 0.00113* | 0.00184*** | 0.00238** | 0.00312*** | 0.00312*** | 0.00325*** |
| | (0.80) | (1.67) | (2.72) | (2.32) | (2.72) | (2.90) | (2.99) |
| Balance | 0.00002 | 0.00003 | 0.00001 | 0.00012 | 0.00018 | -0.00087 | -0.00354*** |
| | (0.09) | (0.11) | (0.03) | (0.16) | (0.17) | (-0.83) | (-3.90) |
| Debt | 0.00002 | 0.00006 | 0.00014* | 0.00026** | 0.00035** | 0.00034** | 0.00021 |
| | (0.62) | (0.99) | (1.79) | (2.01) | (2.12) | (2.06) | (1.16) |
| Unemployment | 0.00070** | 0.00172*** | 0.00397*** | 0.00890*** | 0.01392*** | 0.01871*** | 0.02243*** |
| | (2.00) | (3.55) | (6.93) | (10.23) | (12.97) | (14.46) | (15.17) |
| Constant | 0.00333 | 0.00297 | -0.00659 | -0.03574*** | -0.06165*** | -0.08169*** | -0.08371*** |
| | (0.98) | (0.63) | (-1.17) | (-3.59) | (-5.11) | (-6.58) | (-6.06) |
| N | 2617 | 2617 | 2580 | 2426 | 2266 | 2107 | 1953 |
| R-Squared | 0.00877 | 0.02273 | 0.04704 | 0.09203 | 0.14573 | 0.18688 | 0.21643 |

Table 1.33: This table reports the results of the panel predictive regressions of future growth rates of **industrial production** on our political indicators plus the control variables. We run different models with several horizons in our predictive regressions: we start from predicting (out of sample) the 3-month future growth rate until the 5-year future growth rate. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country and time fixed effects**. Standard errors are bootstrapped with 5,000 iterations.

| | IP 3m | IP 6m | IP 1y | IP 2y | IP 3y | IP 4y | IP 5y |
|---|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00005 | -0.00012*** | -0.00022*** | -0.00032*** | -0.00041*** | -0.00040*** | -0.00051*** |
| | (-1.54) | (-2.95) | (-4.95) | (-5.22) | (-5.60) | (-4.43) | (-5.36) |
| Stability res | 0.00044 | 0.00156* | 0.00300*** | 0.00480*** | 0.00696*** | 0.00689*** | 0.00838*** |
| | (0.60) | (1.67) | (3.31) | (3.57) | (4.13) | (3.67) | (4.23) |
| GDP | -0.07437** | -0.08552** | -0.00062 | -0.01462 | 0.01156 | -0.01024 | -0.02062 |
| | (-2.43) | (-2.12) | (-0.02) | (-0.25) | (0.18) | (-0.14) | (-0.23) |
| Unemployment | 0.00045 | 0.00086* | 0.00124*** | 0.00346*** | 0.00648*** | 0.00915*** | 0.01086*** |
| | (1.22) | (1.71) | (2.61) | (5.09) | (7.36) | (8.81) | (9.46) |
| Balance | 0.00030 | 0.00050 | 0.00073* | 0.00156** | 0.00131 | -0.00083 | -0.00508*** |
| | (1.11) | (1.37) | (1.72) | (2.26) | (1.29) | (-0.86) | (-5.32) |
| Debt | 0.00009** | 0.00020*** | 0.00047*** | 0.00088*** | 0.00117*** | 0.00127*** | 0.00116*** |
| | (2.07) | (3.28) | (6.08) | (6.69) | (7.28) | (8.28) | (7.55) |
| Slope | -0.00024 | -0.00009 | -0.00013 | 0.00008 | 0.00067 | 0.00141 | 0.00267*** |
| | (-0.48) | (-0.14) | (-0.27) | (0.12) | (0.80) | (1.55) | (2.71) |
| Currency res | 0.01585 | -0.00973 | 0.05138** | 0.04529 | 0.01767 | 0.00624 | 0.03932 |
| | (0.63) | (-0.38) | (2.38) | (1.50) | (0.45) | (0.15) | (0.86) |
| Constant | 0.00372 | 0.00388 | 0.01155 | 0.03106 | 0.04828* | 0.06391** | 0.08878** |
| | (0.50) | (0.35) | (1.20) | (1.42) | (1.95) | (1.97) | (2.29) |
| N | 2603 | 2603 | 2567 | 2416 | 2260 | 2105 | 1953 |
| R-Squared | 0.14165 | 0.21533 | 0.45261 | 0.47688 | 0.48378 | 0.50629 | 0.56587 |

Table 1.34: This table reports the results of the panel predictive regressions of future growth rates of the **aggregate dividend yield** on our political indicators plus the control variables. We run different models with several horizons in our predictive regressions: we start from predicting (out of sample) the 3-month future growth rate until the 5-year future growth rate. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country fixed effects**. Standard errors are bootstrapped with 5,000 iterations.

| | DY 3m | DY 6m | DY 1y | DY 2y | DY 3y | DY 4y | DY 5y |
|---|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00054*** | -0.00054*** | -0.00054*** | -0.00054*** | -0.00054*** | -0.00055*** | -0.00058*** |
| | (-5.44) | (-5.37) | (-5.39) | (-5.03) | (-4.97) | (-4.76) | (-4.41) |
| Stability res | 0.01018*** | 0.01024*** | 0.01012*** | 0.01030*** | 0.01045*** | 0.01047*** | 0.01051*** |
| | (5.38) | (5.45) | (5.41) | (5.59) | (6.40) | (5.76) | (5.28) |
| GDP | 0.08867 | 0.15059 | 0.17570* | 0.20239* | 0.23573** | 0.25049** | 0.24311* |
| | (0.82) | (1.45) | (1.74) | (1.94) | (2.19) | (2.12) | (1.99) |
| Unemployment | 0.00314** | 0.00302** | 0.00303** | 0.00332** | 0.00358*** | 0.00380*** | 0.00474*** |
| | (2.24) | (2.17) | (2.18) | (2.46) | (3.20) | (2.99) | (3.24) |
| Balance | -0.00026 | -0.00031 | -0.00032 | -0.00014 | 0.00018 | 0.00029 | 0.00048 |
| | (-0.27) | (-0.32) | (-0.33) | (-0.14) | (0.20) | (0.30) | (0.48) |
| Debt | -0.00007 | -0.00006 | -0.00007 | -0.00005 | 0.00001 | 0.00001 | -0.00012 |
| | (-0.40) | (-0.38) | (-0.40) | (-0.26) | (0.08) | (0.05) | (-0.62) |
| Slope | 0.00502*** | 0.00498*** | 0.00498*** | 0.00495*** | 0.00512*** | 0.00513*** | 0.00524*** |
| | (2.95) | (2.96) | (2.95) | (2.83) | (2.79) | (2.78) | (2.90) |
| Currency res | -1.17100*** | -1.17631*** | -1.17480*** | -1.17994*** | -1.22528*** | -1.22095*** | -1.21444*** |
| | (-14.41) | (-14.59) | (-14.52) | (-14.68) | (-15.11) | (-14.58) | (-14.49) |
| Constant | 0.01924 | 0.01910 | 0.01921 | 0.01593 | 0.01090 | 0.00992 | 0.01146 |
| | (1.24) | (1.24) | (1.25) | (1.04) | (0.79) | (0.62) | (0.62) |
| N | 3006 | 3006 | 3006 | 2858 | 2703 | 2548 | 2394 |
| R-Squared | 0.25371 | 0.25570 | 0.26045 | 0.26085 | 0.26170 | 0.25656 | 0.25347 |

Table 1.35: This table reports the results of the panel predictive regressions of future growth rates of the **aggregate dividend yield** on our political indicators plus the control variables. We run different models with several horizons in our predictive regressions: we start from predicting (out of sample) the 3-month future growth rate until the 5-year future growth rate. "Stability res" refers to political instability, which has been orthogonalized with respect to economic policy. Likewise, "Currency res" represents the quarterly depreciation rate of the home currency with respect to the US dollar, which has been orthogonalized with respect to policy and instability. GDP is expressed as the percentage growth rate with respect to the previous quarter. Unemployment, primary balance and the stock of national debt are in percentage terms with respect to the GDP of the country. The slope of the term structure is computed as the difference between the 10-year and the 3-month rates of government bonds. The sample comprises **42 markets** in the period 1992-2016. We control for **country and time fixed effects**. Standard errors are bootstrapped with $5,000$ iterations.

| | DY 3m | DY 6m | DY 1y | DY 2y | DY 3y | DY 4y | DY 5y |
|---|---|---|---|---|---|---|---|
| | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* | $\beta$ *(t-Stat)* |
| Policy | -0.00035*** | -0.00035*** | -0.00035*** | -0.00035*** | -0.00035*** | -0.00035*** | -0.00035*** |
| | (-3.69) | (-3.69) | (-3.69) | (-3.52) | (-3.31) | (-3.05) | (-2.82) |
| Stability res | 0.00693*** | 0.00707*** | 0.00692*** | 0.00697*** | 0.00705*** | 0.00688*** | 0.00682*** |
| | (3.81) | (3.86) | (3.84) | (3.78) | (3.79) | (3.40) | (3.00) |
| GDP | 0.08141 | 0.09343 | 0.12174* | 0.15484** | 0.15890** | 0.16017** | 0.12668* |
| | (1.12) | (1.36) | (1.84) | (2.46) | (2.39) | (2.28) | (1.80) |
| Unemployment | 0.00114 | 0.00112 | 0.00116 | 0.00137 | 0.00185* | 0.00177 | 0.00195 |
| | (0.91) | (0.90) | (0.92) | (1.14) | (1.82) | (1.43) | (1.24) |
| Balance | 0.00048 | 0.00044 | 0.00045 | 0.00072 | 0.00098 | 0.00099 | 0.00105 |
| | (0.51) | (0.47) | (0.48) | (0.78) | (1.16) | (1.12) | (1.08) |
| Debt | 0.00016 | 0.00016 | 0.00015 | 0.00017 | 0.00018* | 0.00020* | 0.00010 |
| | (1.55) | (1.55) | (1.52) | (1.53) | (1.79) | (1.84) | (0.88) |
| Slope | 0.00362** | 0.00362** | 0.00359* | 0.00359* | 0.00370* | 0.00371** | 0.00384** |
| | (2.04) | (2.03) | (2.02) | (1.99) | (2.01) | (2.06) | (2.21) |
| Currency res | -0.86175*** | -0.86695*** | -0.86421*** | -0.85799*** | -0.88625*** | -0.87597*** | -0.86860*** |
| | (-13.47) | (-13.40) | (-13.54) | (-13.36) | (-12.98) | (-12.92) | (-12.68) |
| Constant | -0.04474* | -0.04453* | -0.04531* | -0.04987** | -0.05509** | -0.05516** | -0.04955* |
| | (-1.86) | (-1.86) | (-1.88) | (-2.09) | (-2.47) | (-2.37) | (-1.97) |
| N | 3006 | 3006 | 3006 | 2858 | 2703 | 2548 | 2394 |
| R-Squared | 0.63919 | 0.64325 | 0.64206 | 0.64730 | 0.64638 | 0.64980 | 0.65376 |

# Chapter 2

# Tail relation between return and volume in the US stock market: an analysis based on extreme value theory*


## Abstract

Using daily data of the SP 500 index from 1950 to 2015, we investigate the relation between return and transaction volume in the statistical distribution tails associated with booms and crashes in the US stock market. We use extreme value theory (peaks-over-threshold method) to study the extreme dependence between the two variables. We show that the extreme correlation between return and volume decreases as we consider larger events in both the left and right distribution tails. From an economic viewpoint, this paper contributes to a better understanding of the activity of market participants


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during extreme events. Our empirical result is consistent with the economic explanation by Gennotte and Leland (1990) of extreme price movements based on misinterpretation of trades by market participants.

## 2.1 Introduction

This paper investigates the relation between return and transaction volume during stock market booms and crashes in the US market. We document how the statistical relation between these two variables changes when considering extreme events. The usual stylized fact about the relation between return and transaction volume (see for example the survey by Karpoff (1987)) is that there is a positive correlation between volumes and the absolute value of returns. However, Balduzzi et al. (1996) found that the correlation disappears when focusing on extreme price movements; their analysis was based on simple statistical regressions. In this paper, the tail relation between return and transaction volume is reinvestigated by using extreme value theory, which is the appropriate statistical tool to deal with extremes. From an economic point of view, this paper contributes to a better understanding of the activity of market participants during extreme events.

The paper is organized as follows: Section 2.2 reviews existing works about the relation between return and transaction volume. Section 2.3 presents our modeling approach: first, we select extremes with the peaks-over-threshold method, focusing on large positive and negative returns. We then estimate the bivariate distribution of extremes by fitting a general Pareto distribution for each marginal distribution and a Gumbel copula to model the dependence as done in Longin and Solnik (2001). Section 2.4 presents our empirical results and the robustness checks. Section 2.5 relates our results to economic models of market crashes. Section 2.6 concludes.

## 2.2 Existing work about the (tail) return-volume relation

We first review key papers in the literature about the return-volume relation for the US stock market. We then focus on existing papers dealing with the return-volume relation during extreme events contained in the distribution tails.

### 2.2.1 Return-volume relation

Karpoff (1987) showed that volume is positively related to the magnitude of the price change but also to the direction of the price change (heavier volume in bull markets and lighter volume in bear markets). Gallant et al. (1992) also found that there is a contemporaneous positive relation between trading volumes and (absolute) price changes, and between volume and price volatility. Another topic that has been largely investigated in the literature is the causality effects from volume to price changes and vice versa. Hiemstra and Jones (1994) provided evidence of significant bidirectional nonlinear Granger causality between return and volume. The dynamic return-volume relation was also studied by Llorente et al. (2002); they developed a theoretical model that separates hedging trades from speculative trades, and showed that the return-volume relation is influenced by the degree of informed trading.

### 2.2.2 Tail return-volume relation

The return-volume relation associated with extreme events was first studied by Balduzzi et al. (1996). In their paper, they focused on annual minimal returns (the lowest daily return observed during the year) and distinguished "crashes" (large minimal returns in absolute terms) and "non-crashes" (small minimal returns in absolute terms). They ran a regression analysis of annual minimal returns on contemporaneous volumes, finding that the regression line was flatter for crashes than for non-crashes. The main result of their research was the following: for minimal returns associated with non-crashes, return shows a strong correlation with transaction volume. However, the return-volume relation breaks down for crashes: a given price crash may translate into quite different trading volumes. Empirically, the correlation between minimal returns and transaction volume is -0.06 for crashes and -0.39 for non-crashes. In our paper, we use extreme value theory with the peaks-over-threshold method: bivariate exceedances correspond to pair observations higher than given thresholds. Such a method allows one to obtain extreme observations of returns and volumes on the same day. It is therefore the appropriate method to study the contemporaneous tail return-volume relation.

An alternative approach to the peak-over-threshold method is the block-maxima method, which considers the maximum of each variable: the highest observation over a given time-period. Such an approach has been introduced in finance by Longin (2000) and applied by Marsh and Wagner (2004) to study the return-volume relation using monthly extremes. However, the block-maxima method presents several drawbacks: 1) the time-period over which extremes are selected may not be optimal for efficient statistical estimation; 2) another parameter called the extremal index has to be introduced to take into account the dependency in the data; and 3) over a given time-period, an extreme in returns and an extreme in volumes may occur on different days. The well-established peak-over-threshold method deals with all these issues (see Embrechts et al (1997) for more details).

## 2.3 Modeling approach

In this section, we present our modeling approach for the bivariate distribution of extremes. We fit a general Pareto distribution for each marginal distribution and a Gumbel copula to model the dependence as done in Longin and Solnik (2001). We implement the peaks-over-threshold method to extract extreme returns and volumes: we take a threshold for returns (defined as percentage points) and we select accordingly all returns that lie above (below) this threshold for positive (negative) extremes. This threshold denoted by $\theta^{ret}$ corresponds to a tail probability $p$ of the distribution of returns; we use the same probability level $p$ to compute the threshold for volumes $\theta^{vol}$. The excess distribution of a random variable $X$ over a threshold $\theta$ associated to the tail probability $p$, denoted by $F_X^\theta$, can be expressed as

$$F_X^\theta = P\left(X - \theta \leq x \mid X > \theta\right) = \frac{F_X(x+\theta) - F_X(\theta)}{1 - F_X(\theta)} \tag{2.1}$$

Following Tawn (1988) and Ledford and Tawn (1996), the distribution of univariate exceedances, $F_X(\theta)$, can be asymptotically approximated by the generalized Pareto distribution defined by:

$$G_X^\theta(x) = 1 - p\left(1 + \xi\,\frac{(x-\theta)}{\sigma}\right)^{-\frac{1}{\xi}} \tag{2.2}$$

where $\xi$ is the tail index and $\sigma$ is the dispersion parameter. Then, we model the dependence between bivariate exceedances with a Gumbel copula function:

$$F_{X_1,X_2}(x_1,x_2) = C_\alpha\left(F_{X_1}(x_1), F_{X_2}(x_2)\right) = e^{\left[-\log\left(-\frac{1}{\log G_{X_1}^{\theta_1}(x_1)}\right)^{-\frac{1}{\alpha}} - \log\left(-\frac{1}{\log G_{X_2}^{\theta_2}(x_2)}\right)^{-\frac{1}{\alpha}}\right]^{\alpha}} \tag{2.3}$$

The Gumbel copula is based on the logistic function, and its estimation is performed via maximum likelihood with censored data. Tiago de Oliveira (1973) showed that the extreme correlation coefficient $\rho$ can be derived from the dependence parameter $\alpha$ of Equation (2.3):

$$\rho = 1 - \alpha^2 \tag{2.4}$$

The extreme correlation $\rho$ is the key variable in our analysis of the tail relation between return and volume in the US stock market.

## 2.4 Empirical results

This section presents our empirical results. We first discuss the data and data adjustments, then we present the main result of our research, and finally we list the robustness checks.

### 2.4.1 Data and data adjustment

We analyze a sample that comprises daily data for the SP 500 index from January 3, 1950 to September 30, 2015 (16,542 observations). For each day, data include the index return defined as the percentage log change in the index closing price, and volume defined as the transaction volume of all index stocks traded on different markets. We use the CSI database, which is the most reliable database to incorporate transaction data from all trading venues. We apply the data adjustment procedure developed by Gallant et al. (1992) in order to obtain stationary time-series for returns and volumes (see Appendix 2 for details). Data are adjusted for the presence of linear and squared trends in the mean and variance of time-series and various seasonality effects (day-of-the-week, month, special tax periods).

### 2.4.2 Main result

Estimation results are reported in Figure 2.1. This figure gives the maximum likelihood estimates of the parameters of the bivariate distribution of return and transaction volume exceedances. Panel A is for negative return exceedances and positive volume exceedances, and Panel B for positive return exceedances and positive volume exceedances. Data for returns and volumes are first adjusted to obtain stationary time-series. Return and volume exceedances are defined with a threshold $\theta$; both fixed and optimal levels are used for $\theta$. For the threshold used for returns $\theta^{ret}$, fixed levels (defined as percentage points) are: 0%, 1%, 2%, 3%, 4%, and 5% (above or below the mean). By construction, the tail probability for volumes $\rho_{vol}$ is set equal to the tail probability for returns $\rho_{ret}$; the threshold used for volumes $\theta^{vol}$ is then deduced from the tail probability for volumes $\rho_{vol}$. Optimal levels are computed using the procedure developed by Jansen and de Vries (1991); these levels are given on the last line of each panel. We report in the figure the following parameter estimates: the threshold $\theta$, the tail probability $p$, the dispersion parameter $\sigma$ and the tail index $\xi$ for both returns and volumes, the dependence parameter $\alpha$ of the Gumbel copula and the extreme correlation$\rho$.

Looking at the marginal distribution for returns, the tail index satisfies the relation $\xi > 0$ for both negative extreme returns (+0.248 with an optimal threshold of $-1.74\%$) and positive extreme returns (+0.140 with an optimal threshold of +1.87%). Therefore, the asymptotic distribution of extremes is a Fréchet extreme value distribution associated with a fat-tailed distribution of returns. The same remark applies to the marginal distribution of transaction volumes (+0.076 with an optimal threshold of 23.115).

Looking at the dependence between extreme returns and volumes using fixed thresholds, the extreme correlation $\rho$ declines as we move towards both the left and right tails. Considering negative return exceedances, with an optimal threshold of $-1.74\%$ for returns and an optimal threshold of 23.115 for high volumes, the extreme correlation is equal to +0.164. Considering positive return exceedances, with an optimal threshold of +1.87% for returns and an optimal threshold of 23.115 for high volumes, the extreme correlation is equal to +0.241. This result is also illustrated in Figure 2.2, which represents the structure of extreme correlation for fixed thresholds used to define extreme returns ranging from $-5\%$ to $0\%$ for negative returns and $0\%$ to $+5\%$ for positive returns. In both cases, the correlation decreases when considering larger events in the left and right distribution tails. The figure also shows that the structure is quite symmetric considering negative and positive return exceedances.

### 2.4.3 Robustness checks

In this subsection, we discuss the robustness of our result to different specifications: data adjustment methods and behavior over time.

As already noted, in order to apply extreme value theory, it is important to work with stationary time-series. To deal with this issue we used the standard procedure developed by Gallant et al. (1992). Furthermore, as highlighted by McNeil and Frey (2000), it is also important to take into consideration the heteroskedasticity in financial data reflecting volatility clustering and the appearance of extremes around the same time. We follow their two-step procedure by first estimating a NA-GARCH(1,1) process to take into account volatility persistence and asymmetry as well, by then constructing residuals obtained by dividing adjusted returns and volumes by the square root of their conditional variance, and finally by estimating the bivariate extreme value distribution with these residuals. The estimates of the extreme correlation, when moving towards the tails, were even lower, reinforcing our results.

Our result was obtained for the time-period 1950-2015. Although extreme events in financial markets tend to appear on a regular basis, changes in the economic and financial environment may translate into changes in the return-volume relation. In order to check the stability of this result over time, we estimated the extreme correlation over different sub-periods. We still found the same pattern for the extreme correlation structure: extreme correlation decreases when we consider larger events in both the left and right distribution tails. Our main finding is therefore stable and persistent over time.

## 2.5 Economic implication

Our empirical study sheds some light on the economic models of market booms and crashes proposed in the academic literature. In this section, we review such models and analyze their implication for the tail return-volume relation. We choose models that deal with different aspects of information in financial markets: overreaction, asymmetry, and misinterpretation. The arrival of new information is one of the main determinants of market price evolution. However, French and Roll (1986) assert that trying to explain market crashes with available and tangible information might be very hard. In the same line, Cutler et al. (1989) study the largest postwar price movements of the SP500 index and report that such market movements are not related to any dramatic news. According to Shiller (1987), investors do not react to any hard information during market crashes, but they actually do react to each other, this mechanism being therefore key for extreme events to happen. In contrast with the efficient market hypothesis, De Bondt and Thaler (1985) postulate that investors overreact to new information: they react by trading more than expected when receiving news about the asset value, this overreaction being due to a purely behavioral bias. Transaction volumes are then expected to be even more positively correlated with market returns when considering extreme events.

Asymmetric information among market participants is also a key concept to understand the formation of market prices. Kyle (1985) proposes a model for the price formation process induced by the game between a risk-neutral market maker and a strategic informed trader in the presence of liquidity traders. The informed trader exploits her private information about the liquidation value of the asset by concealing her trading orders behind the activity of liquidity traders. The model implies a positive correlation between prices and volumes: when the informed trader receives private information about the liquidation value of the asset, she will increase her demand for the asset proportionally to the signal received. Thus, she will trade more aggressively when receiving news about an extreme change in the liquidation value of the asset.

Gennotte and Leland (1990) propose a model of market booms and crashes based on the misinterpretation of trades. In their model, some market participants implement trading strategies with positive feedback such as stop-loss strategies used in portfolio insurance. The impact of such mechanical trading rules on market prices may be misinterpreted by other market participants: they may consider these trades as informed while they are actually uninformed. Gennotte and Leland (1990) show that a relatively small amount of misinterpreted uninformed trades can lead to a market crash, the magnitude of which is positively related to the degree of asymmetric information. In their model, extreme price movements can then be associated with either low or high trading volume.

In our paper, we find that the extreme correlation between return and volume is very low in both the left and right distribution tails. This result about the observed tail return-volume relation is consistent with the Gennotte and Leland (1990) model based on misinterpretation, as they show that extreme events can be associated with either low or high transaction volume. On the other hand, our empirical result is not consistent with models of overreaction to news and information asymmetry among market participants as these models imply a positive relation between return and volume.

## 2.6 Conclusion

This paper investigates the relation between return and transaction volume during extreme events contained in the distribution tails. We assess the dependence between returns and volumes in both the left and right tails, looking at the extreme correlation between the two variables. This study documents that the extreme correlation decreases when moving towards the tails; moreover, this correlation turns out to be remarkably lower during extraordinary market conditions than during normal times, meaning that returns and volumes are not highly correlated during stock market booms and crashes. This result is robust with respect to data adjustment methods and behavior over time. Relating our statistical findings to economic models, we find that our empirical result is consistent with the explanation of market crashes by Gennotte and Leland (1990) based on trade misinterpretation.

## 2.7 Appendix 1: Procedure to obtain stationary return and volume

In order to apply extreme value theory, it is important to work with stationary time-series. To deal with this issue we used the 3-step procedure developed by Gallant et al. (1992) reproduced below.

**Step 1**:

First, we de-trend the mean by regressing the raw original series on a set of explanatory variables that take into account the time trends (linear and quadratic) and several seasonality effects,

$$w = X\,\beta + u, \quad \textit{with} \;\; w = r \;\; \textit{or} \;\; v, \tag{2.5}$$

with $w$ being log-returns or log-volumes.

The matrix $X$ comprises the following regressors: a constant term, a dummy variable for each day of the week, except Monday to avoid multicollinearity and without considering Saturdays and Sundays; four dummy variables that refer each to one particular period in January, and that all together cover the 31 days in January (1-7, 8-14, 15-21, 22-31); four dummy variables that refer each to one particular period in December, and that all together cover the 31 days in December (1-7, 8-14, 15-21, 22-31); one dummy variable for each month of the year, except January, February and December to avoid multi-colinearity; two dummy variables to take into account time trends, one linear and one quadratic; four dummy variables, that define, respectively, situations in which there is a gap of 1 day, 2 days, 3 days or 4 days between two consecutive trading days. In total, $X$ comprises 28 regressors, including the constant. The aforementioned regressors are meant to take into account the well-known seasonalities of transaction volume. For the sake of consistency, we apply the same procedure for the return series as well. The two time-trends regressors are excluded from the mean equation of the price changes regressions, whereas they are explanatory variables in the log-volume regression.

**Step 2**:

Second, we de-trend the variance of the time-series by running the subsequent regression,

$$\log u^2 = X^{'}\gamma + \epsilon \tag{2.6}$$

where it has to be noticed that the same set of explanatory variables is used in order to remove the trend from the variance.

**Step 3**:

Third, we perform the following transformation to compute the adjusted time series,

$$w_{adj} = a + b\left(\frac{\hat{u}}{\frac{e^{X^{'}\gamma}}{2}}\right). \tag{2.7}$$

The coefficients $a$ and $b$ in the previous equation are determined by solving a system of two equations with two unknowns, where the adjusted time series is required to have the same mean and variance of the original series.

**Results for returns**:

The figures below show the starting time-series of returns compared to the new adjusted time series obtained by applying the aforementioned procedure. The x-axis represents the number of observations, with 1 referring to the first observation in time (January 3, 1950) and 16,542 being the latest one (September 30, 2015). The y-axis represents returns in the figure on the left, and the adjusted returns on the right.

[ Insert figure 2.3 near here ]

**Results for transaction volumes**:

The figures below show the starting time-series of transaction volume compared to the new adjusted time series obtained by applying the aforementioned procedure. The x-axis represents the number of observations, with 1 referring to the first observation in time (January 3, 1950) and 16,542 being the latest one (September 30, 2015). The y-axis represents the transaction volume in the figure on the left, and the adjusted transaction volume on the right.

[ Insert figure 2.4 near here ]

## 2.8 Appendix 2: Computation of optimal threshold levels

In order to define extremes, an optimal threshold level can be obtained by optimizing the trade-off between bias and inefficiency. To solve this problem, we use the simulation method developed by Jansen and de Vries (1991) and applied by Longin and Solnik (2001) reproduced below. This appendix describes the procedure in detail. The same procedure is applied for returns and volumes. A particular model is assumed. For each simulated time-series of returns or volumes, the optimal number of exceedances (or equivalently the optimal threshold level) is computed. The MSE of simulated optimal numbers of exceedances is then computed to derive the number of exceedances for the observed time-series. The MSE criterion allows one to take explicitly into account the two effects of bias and inefficiency. The mean square error of $S$ simulated observations $\tilde{X}_s$ of the estimator of a parameter $X$ can be decomposed as follows

$$MSE\left((\tilde{X}_s)_{s=1,\dots,S}, X\right) = \left(\overline{X} - X\right)^2 + \frac{1}{S}\sum_{s=1}^{S}\left(\tilde{X}_S - X\right)^2 \qquad (2.8)$$

where $\overline{X}$ represents the mean of $S$ simulated observations. The first part of the decomposition measures the bias and the second part the inefficiency. The procedure can be decomposed in four steps.

First we simulate S time-series containing T observations from Student-t distributions with k degrees of freedom, the integer $k$ ranging from 1 to $K$. The class of the Student-t distributions is chosen to consider different degrees of tail fatness. The lower the degrees of freedom, the fatter the distribution as the tail index $\xi$ is related to $k$ by $\xi = \frac{1}{k}$. For the simulations, we take: S=1,000, T=16,542 and K=10.

For different numbers n of exceedances, we obtain a tail index estimate $\tilde{\xi}_s(n,k)$ corresponding to the sth simulated time-series and to the Student-t distribution with $k$ degrees of freedom. In order to identify the optimal number of exceedances, we focus on the tail index as this parameter models the distribution tails. We choose the values of $n$ ranging from $0.01T$ to $0.20T$ such that proportions from one percent to 20 percent of the total number T of observations are used in the estimation procedure.

For a Student-t distribution with $k$ degrees of freedom and for each number $n$ of exceedances, we compute the MSE of the S tail index estimates, denoted by $MSE\left((\tilde{\xi}_s(n,k))_{s=1,\dots,S}\right)$. As explained by Jansen and de Vries (1991), there is a U-shaped relation between $MSE\left((\tilde{\xi}_s(n,k))_{s=1,\dots,S}\right)$ and $n$, which expresses the trade-off between bias and inefficiency. For high values of $n$, the inclusion of many observations such that some do not belong to the tail but rather to the center of the distribution makes the bias part of the MSE dominate the inefficiency part. On the other hand, for low values of n, the inclusion of few observations makes the inefficiency part of the MSE dominate the bias part as the tail index is badly estimated. We then select the number of exceedances which minimizes the MSE. This number, denoted by $n^*(k)$, is optimal for a Student-t distribution with k degrees of freedom. The optimal number of exceedances is an increasing function of the fatness of the simulated Student-t distribution. The fatter the distribution, the higher the number of exceedances used in the estimation of the tail index as more extreme observations are available.

For the K optimal numbers of exceedances previously obtained by simulation, $n^*(k)_{k=1,\ldots,K}$ we compute the tail index estimates of the observed time-series of actual returns or volumes, denoted by $\tilde{\xi}(n^*(k))$ for $k$ ranging from 1 to $K$. We then select the number of exceedances, for which the corresponding tail index estimate is statistically the closest to the tail index defined in the simulation procedure, that is to say $1/k$ (we consider the p-value of the t-test of the following hypothesis: $\tilde{\xi}(n^*(k)) = 1/k$). This number, denoted by $n^*$, is considered to be the optimal number of exceedances for the distribution of actual returns or volumes.

Figure 2.1: This figure gives the parameter estimates of the bivariate distribution of return and transaction volume exceedances for the S&P 500 index from January 3, 1950 to September 30, 2015 (16,542 observations). The estimation is based on the maximum likelihood method with censored data, developed by Ledford and Tawn (1996). Panel A is for negative return exceedances and positive volume exceedances, and Panel B for positive return exceedances and positive volume exceedances. See Appendix 1 for the details of the statistical estimation procedure. Data for returns and volumes are first adjusted to obtain stationary time-series as discussed in Appendix 2. Return and volume exceedances are defined with a threshold $\theta$; both fixed and optimal levels are used for $\theta$. For the threshold used for returns $\theta^{ret}$, fixed levels (defined as percentage points) are: 0%, 1%, 2%, 3%, 4% and 5%. By construction, the tail probability for volumes pvol is set equal to the tail probability for returns pret; the threshold used for volumes $\theta^{vol}$ is then deduced from the tail probability for volumes. Optimal levels are given on the last line of each panel. Data for returns and volumes are first adjusted to obtain stationary time-series as done in Gallant et al (1992). We report in the figure the following parameter estimates: the threshold $\theta$, the tail probability $p$, the dispersion parameter $\sigma$ and the tail index $\xi$ for both returns and volumes, the dependence parameter $\alpha$ of the Gumbel copula and the extreme correlation $\rho$. Standard errors are given below in parentheses.

**Panel A: Negative return exceedances and positive volume exceedances**

| $\theta^{ret}$ | $p^{ret}$ | $\sigma^{ret}$ | $\xi^{ret}$ | $\theta^{vol}$ | $p^{vol}$ | $\sigma^{vol}$ | $\xi^{vol}$ | $\alpha^{ret/vol}$ | $\rho^{ret/vol}$ |
|---|---|---|---|---|---|---|---|---|---|
| -5% | 0.001 | 1.809 | 0.169 | 26.886 | 0.001 | 1.755 | 0.003 | 0.912 | 0.168 |
| | | (0.556) | (0.208) | | | (0.754) | (0.363) | (0.054) | (0.099) |
| -4% | 0.002 | 1.444 | 0.190 | 25.821 | 0.002 | 1.360 | 0.129 | 0.887 | 0.214 |
| | | (0.323) | (0.163) | | | (0.349) | (0.205) | (0.039) | (0.069) |
| -3% | 0.006 | 0.914 | 0.343 | 24.787 | 0.006 | 1.152 | 0.155 | 0.895 | 0.199 |
| | | (0.164) | (0.151) | | | (0.185) | (0.124) | (0.025) | (0.045) |
| -2% | 0.024 | 0.583 | 0.309 | 23.182 | 0.024 | 1.074 | 0.089 | 0.913 | 0.166 |
| | | (0.047) | (0.064) | | | (0.077) | (0.052) | (0.011) | (0.020) |
| -1% | 0.113 | 0.598 | 0.131 | 21.130 | 0.113 | 1.377 | -0.037 | 0.861 | 0.259 |
| | | (0.019) | (0.023) | | | (0.041) | (0.019) | (0.006) | (0.010) |
| -0% | 0.454 | 0.665 | 0.035 | 18.475 | 0.454 | 2.113 | -0.138 | 0.700 | 0.509 |
| | | (0.010) | (0.010) | | | (0.026) | (0.005) | (0.003) | (0.004) |
| -1.74% | 0.034 | 0.594 | 0.248 | 23.115 | 0.025 | 1.098 | 0.076 | 0.914 | 0.164 |
| | | (0.038) | (0.049) | | | (0.076) | (0.049) | (0.010) | (0.019) |

**Panel B: Positive return exceedances and positive volume exceedances**

| $\theta^{ret}$ | $p^{ret}$ | $\sigma^{ret}$ | $\xi^{ret}$ | $\theta^{vol}$ | $p^{vol}$ | $\sigma^{vol}$ | $\xi^{vol}$ | $\alpha^{ret/vol}$ | $\rho^{ret/vol}$ |
|---|---|---|---|---|---|---|---|---|---|
| +0% | 0.511 | 0.674 | -0.012 | 18.125 | 0.511 | 2.265 | -0.149 | 0.613 | 0.624 |
| | | (0.009) | (0.009) | | | (0.026) | (0.004) | (0.003) | (0.003) |
| +1% | 0.108 | 0.562 | 0.125 | 21.205 | 0.108 | 1.359 | -0.032 | 0.826 | 0.318 |
| | | (0.020) | (0.027) | | | (0.041) | (0.019) | (0.006) | (0.011) |
| +2% | 0.022 | 0.672 | 0.142 | 23.320 | 0.022 | 1.057 | 0.102 | 0.872 | 0.240 |
| | | (0.055) | (0.064) | | | (0.081) | (0.056) | (0.013) | (0.023) |
| +3% | 0.006 | 0.853 | 0.084 | 24.787 | 0.006 | 1.152 | 0.155 | 0.913 | 0.166 |
| | | (0.130) | (0.113) | | | (0.185) | (0.124) | (0.023) | (0.042) |
| +4% | 0.002 | 1.142 | -0.017 | 26.397 | 0.002 | 1.349 | 0.161 | 0.919 | 0.156 |
| | | (0.334) | (0.224) | | | (0.455) | (0.281) | (0.041) | (0.076) |
| +5% | 0.001 | 1.237 | -0.075 | 27.045 | 0.001 | 2.402 | -0.239 | 0.909 | 0.173 |
| | | (0.535) | (0.354) | | | (1.185) | (0.429) | (0.056) | (0.102) |
| +1.87% | 0.027 | 0.651 | 0.140 | 23.115 | 0.025 | 1.098 | 0.076 | 0.871 | 0.241 |
| | | (0.047) | (0.055) | | | (0.076) | (0.049) | (0.012) | (0.021) |

Figure 2.2: This figure represents the structure of the extreme correlation between return and transaction volume exceedances for the S&P 500 index from January 3, 1950 to September 30, 2015 (16,542 observations). The extreme correlation between return and volume is obtained from the estimation of the bivariate distribution modeled with the logistic function. The value of the threshold $\theta$ used to define return exceedances ranges from $-5\%$ to $+5\%$ (percentage points).

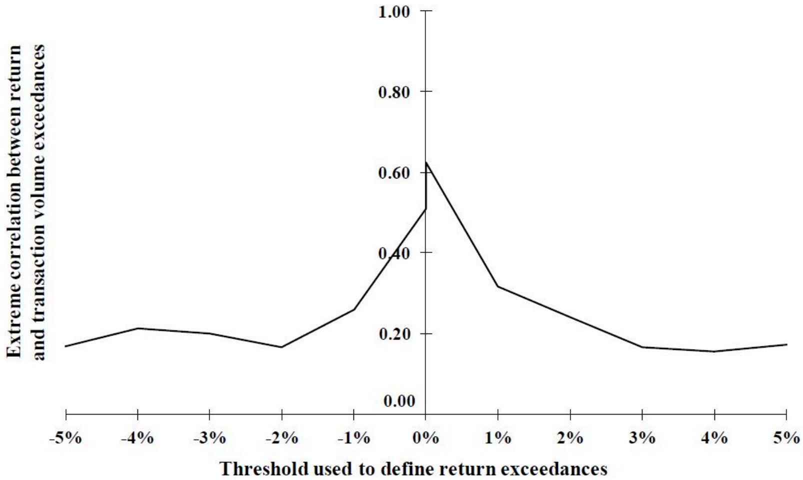



Figure 2.3: This figure shows the result of the stationarity procedure for returns. On the left, we report the returns distribution before the application of the stationarity procedure, on the right after.

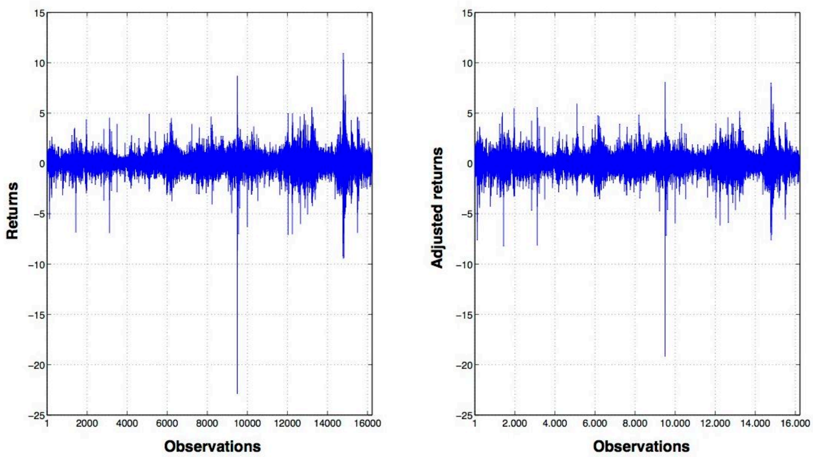
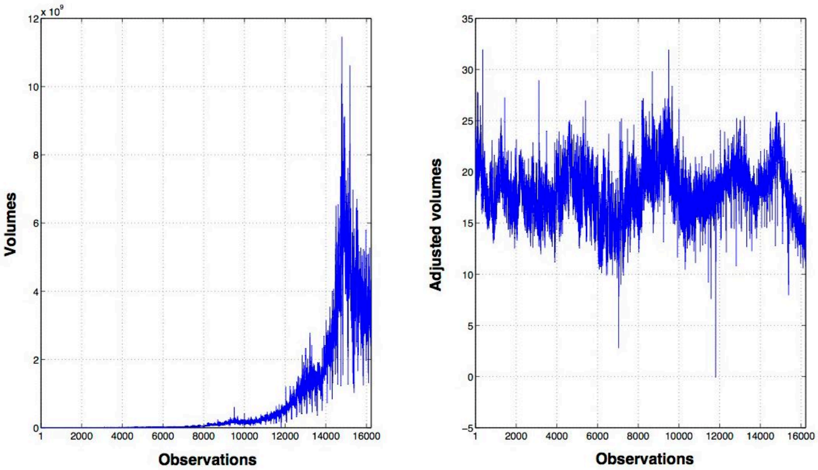


Figure 2.4: This figure shows the result of the stationarity procedure for returns. On the left, we report the returns distribution before the application of the stationarity procedure, on the right after.



# Chapter 3

# Forecasting non-linear time-series: theory and application to the US GDP *


## Abstract

The vast majority of financial and economic time-series exhibits sharp deviations from a two-moment setting, including skewed and leptokurtic distributions in addition to Markov switches. An enlightening example is the GDP, which has been extensively modeled by postulating various switching dynamics between different phases of the business cycle. However, all such approaches require non-verifiable assumptions on the structure of the underlying stochastic process, whereas most often the researcher cannot precisely detect the exact form of the data-generating process. To deal with non-linear and non-gaussian dynamics, we develop a non-parametric forecasting algorithm that employs the entropy of the forecasting error distribution as cost function. The entropy allows to take into account all the information embedded in the time-series and thus in all its higher moments. We compare its performance with respect to a quadratic cost function on simulated processes as well as on the US GDP. We establish the stochastic dominance


*This chapter is based on a paper co-authored by Stefano Galluccio (Co-Founder & Managing Partner - Incipit Capital Partners LLP, London) and Giovanni Pagliardi (ESSEC Business School, Paris). This research has been supervised by Professor Andrea Roncoroni (ESSEC Business School, Paris) during my PhD in the finance department at ESSEC. The experiments shown in this chapter will be used to write a paper that will also incorporate new theoretical results.

of the entropic algorithm with respect to the mean-square-error technique, in that *(i)* if the model is correctly specified in a totally linear and gaussian setting, the entropic estimator attains the same forecasting accuracy of the quadratic estimator, *ii)* in case of model mis-specification in a non-linear and non-gaussian environment, the entropic algorithm strongly outperforms the quadratic one on a variety of target functionals, and *iii)* the higher forecasting precision is proportional to the degree of non-linearities and non-normality present in the data.

## 3.1 Introduction

It is well known that economic and financial time-series are characterized by non-linear and non-gaussian dynamics. Clements et al. (1998) survey the extant literature providing evidence that great attention has been given by researchers over the years to model financial or economic time-series that are known to be generated by non-linear and non-gaussian stochastic processes. Among others, some enlightening examples are given by stock prices, especially at high frequencies, option prices, GDP growth rates and industrial production.

Several different types of non-linearities can characterize the data-generaring process, hereinafter DGP. First, the DGP might not be of the form of a simple linear autoregressive process like $y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ... + \alpha_p y_{t-p} + \varepsilon_t$, but it can rather be a non-linear function of some of the past observations, as, for instance, $y_t = \alpha_0 + \alpha_1 y_{t-1} y_{t-2} + \alpha_2 y_{t-2} y_{t-3} + \varepsilon_t$. Second, the process may present Markov switches from a state to another according to the dynamics of some latent state variables. Third, the form of the DGP may change over time, due to a structural break and/or a sudden event that drastically impacts the economic environment. Fourth, even in the speficic case of a two-state Markov switch, the dynamics of the process in either or each of the two states may change over time. In a certain state the process can well be linear, yet switching to non-linear dynamics in the same state after that an event occurs. Last but not least, the idiosyncratic error term might be gaussian over a certain time period, whereas afterwards the impact of extreme events could lead the series to sharply deviate from a normal distribution and to be better modeled by a non-gaussian noise encompassing its skewed and leptokurtic behavior.

This sheds light on a key aspect: how difficult, and most often impossible, it is to correctly identify the distributional form of the stochastic process underlying the observed time-series. The extant literature offers a vast number of attemps to model an economic variable of interest postulating certain dynamics for the DGP by means of non-verifiable assumptions. The model would be however invalid if these assumptions were not satisfied in reality. In addition, the specification of a particular assumption on which the model is based implies that it should hold in any economic condition. On the contrary, history tells us that changes in the economic environment do occur, such that certain assumptions may hold in a particular time-period but not in another. As a consequence, the validity of predictive and forecasting models that hinge on such economic assumptions is also questioned. Not being able to observe the dynamics of the DGP is the main reason for which it would be most useful to develop a methodology that can exploit all the information embedded in the observed time-series that displays a non-linear and non-gaussian behavior, without the need to specify a set of assumptions that cannot be verified or that may not hold in all economic conditions.

In that respect, the GDP is an enlightening example. Modelling and predicting its non-linear dynamics has been attracting the attention of researchers for a long time, due to the relevance of being able to correctly model and predict the dynamics of the business cycle. Hamilton (1989) is the pioneering work and benchmark paper in this field. He puts forward a novel econometric methodology designed for the estimation of a two-state Markov-switching model and applies it to the estimation of the US GDP. His model is based on the assumption that the economy can be in either of two states: expansion or contraction. Accordingly, the author fits a two-state Markov model where in each state the growth rate of GDP follows a linear AR(4) process. Following this pioneering and groundbreaking work, researchers have tried to relax some assumptions on which the model by Hamilton (1989) hinges.

The first key assumption is that the economy can be in either of two states only. However, the assumption of the economy switching only from a state of expansion to recession or *vice versa* is non-testable in practice, depends on how we define expansions and contractions, and has been therefore questioned in the literature. Sichel (1994) shows that recessions are typically followed by high-growth recovery phases that push output back to its prerecession level. He claims that postwar fluctuations in real output in the United States have consisted of three sequential phases rather than two: contractions, high-growth recoveries, and moderate-growth periods following recoveries. Accordingly, the author argues that it seems more suitable to fit a three-state Markov model, able to capture and separate these three phases of the business cycle. As a matter of fact, one could proceed along the path traced by this strand of research by postulating other dynamics for the processes in each state or could fine-tune the estimation by adding other intermediate states. However, the DGP would still be unobservable and impossible to be precisely identified.

The conclusion is that arguing that the GDP follows a Markov model characterized by two, three or a different number of states is purely and merely driven by economic intuition, which is an assumption that may not be universally correct. The GDP could switch more clearly between two states only in certain periods of time, then a third state could be disentangled over a particular time-period characterized by some peculiar economic conditions. Moreover, one can never be sure that in the future the economy will follow the same patterns observed in the past. As a matter of fact, Kim et al. (1999) finds a non-linearity in the series of the US GDP given by a structural break occurred in 1984, after which the difference in growth rates for the recession and expansion phases decreased. This confirms that the behavior of the GDP could change from a period to another, such that identifying the process that best fits the data could be even more puzzling. The effectiveness of these methods that have been developed so far relies on how these economic intuitions are suitable and/or correct. In addition, another problem is that every time that one needs to analyze other real economic or financial time-series, he/she would need to specify another set of assumptions or simplifications to decide which model is best to fit and forecast the data. It is therefore much easier and most useful to develop a fully non-parametric approach which takes into account *all* the information contained in that series, without arbitrarily guessing the process underlying the latter.

To further corroborate our statement, we could mention many examples in economics and finance where the assumptions aiming to overcome the impossibility to observe the DGP could lead to model mis-specification. For instance, Gray (1996) puts forward a three-state Markov model but for short-term interest rates. In this framework, Markov-switching models turn out to be more flexible than single-regime models in that they allow the researcher to incorporate a different speed of mean-reversion to a different a long-run mean at different times throughout the sample period. Again, this choice is motivated by an economic intuition that may be inaccurate or that could only partially be true. The economic explanation stems from the change in monetary policy implemented by the FED between 1979 and 1982: the central bank deviated from targeting interesting rates to using non-borrowed reserves as a new target instrument for monetary policy. This led to a period of unprecedented interest rate volatility.

Furthermore, the paper asserts that other periods of high volatility of interest rates corresponded to main changes in the economic environment, due to the OPEC oil crisis, the October 1987 stock market crash and wars involving the US. According to the author, these main changes of the economy affect the dynamics of interest rates and justify the need to apply Markov models. However, it is not clear if and how it is feasible to *predict* interest rates if other relevant changes will occur in the future and how reliable models based on these assumptions can be over time. Once again, a non-parametric forecasting algorithm that extracts all the information embedded in that specific time-series observed would be most useful to overcome these issues.

A second problematic assumption concerns the choice of the stochastic processes by means of which the behavior of the GDP is approximated during each of the states. These processes are usually chosen to be linear, as in Hamilton (1989), where two AR(4) processes are fitted for each of the two states. However, these processes may well be non-linear, in that during a recession or an expansion the GDP could fluctuate showing some non-linear dependency with its values in the previous quarters. The choice of the stochastic processes best describing the data at our disposal is thus an open issue, which may lead to different conclusions. Interestingly, Engel (1994) tests the forecasting ability of the Markov-switching model on exchange rates and claims that if exchange rates follow a two-state Markov switching model at quarterly frequency, they will not generally also follow a two-state Markov process at a different frequency, *i.e.* monthly. This poses a problem in that the researcher always has to guess the most suitable form of the estimator, which can even vary by simply changing the granularity of the data.

A third assumption underlying Hamilton (1989)'s model concerns the probabilities of switching from a state to another, which are supposed to be constant over time. However, several papers have tried to go further in the problem of fitting a Markov model to the series of the GDP by letting these transition probabilities vary over time. Durland et al. (1994) provides evidence of asymmetry between contractions and expansions, revealing the presence of a strong duration dependence associated with postwar recessions than with expansions. Diebold et al. (1996) extends the model by Hamilton (1989), relaxing the assumption of constant transition probabilities and allowing the probabilities driving these occasional but recurrent regime shifts to depend on the underlying economic fundamentals. Proceeding along the same path, Perez-Quiros et al. (2000) also claims that assuming the constant transition probabilities is an oversimplification and lets the probability of staying in a state depend on the duration of the state as well as on other conditioning information.

In order to cope with all the aforementioned issues, we propose an entropic forecasting algorithm that is distribution-free and does not require any assumption about the DGP, since its main feature is the ability to effectively capture all the information embedded in the time-series. Our forecasting methodology takes the form of a linear projection of past observations in time. Therefore, the model does not require to estimate any parameter but only the weights attached to any past lag included in the linear projection. Our choice of a linear projection is motivated by several factors. First, one could argue that forecasting with a linear projection if we know that the time-series is most likely generated by a process with some non-linear dynamics could not be the optimal approach. However, we can never know which exact form the process has and which kind and degree of non-linearity is present in the data. Fitting a particular non-linear model rather than any of the other possible non-linear specifications to start with would be a difficult goal, most likely leading again to model mis-specification.

Furthermore, a well-known issue with any application of non-linear models is the problem of overfitting, as explained by Bradley et al. (2004). The paper shows that non-linear models often have a good in-sample fit but poor out-of-sample performance. In addition, Bradley et al. (2004) underscores that linear models usually display remarkable predictive ability, even in cases when the underlying stochastic process is characterized by non-linear dynamics, arguing that this is the main reason why linear time-series models in the tradition of Box and Jenkins have been extensively studied and applied over the years. For these reasons, we make use of a linear projection where the weights of each past lag are computed by minimizing the entropy of the forecasting error, hence taking into account all the information present in the particular data observed, yet keeping the model simple, tractable and applicable to any time-series, any market condition and any time-period.

We contribute to the literature by describing an entropic forecasting algorithm which is particularly useful when dealing with financial and economics time-series which are typically characterized by non-gaussian and non-linear dynamics. We show how much an entropic cost function can lead to improvements in the forecasting accuracy with respect to a quadratic cost function as the MSE in such a non-linear and non-gaussian setting. Moreover, we contribute to the literature by showing on simulated stochastic processes that such a non-parametric technique becomes most useful when the form of the data generating process is not known and performs well under model mis-specification. Moreover, we contribute to the economics literature by showing how to non-parametrically and accurately forecast the series of the GDP without the need of any restrictive or unverifiable assumption.

The remainder of this paper is structured as follows. Section 3.2 reviews the extant literature and gives the theoretical justification to the use of the entropy as a cost function, highlighting the main benefits that it conveys with respect to a quadratic criterion. Section 3.3 describes the model that we apply. Section 3.4 presents the results on simulated stochastic processes and Section 3.5 describes the results on the US GDP series. Section 3.6 concludes.

## 3.2 Theoretical Justification and Literature Review

The mean square error, hereinafter MSE, is one of the most applied cost functions in statistics and economics. Karlin (1958) and Rao (1980) show that the common choice of the mean square error as cost function is due to two main elements. First, denoting by $\phi(x)$ the estimator, under the condition that the latter is unbiased, the

MSE can be interpreted as the variance of $\phi(x)$, which is the most used quantity to measure the volatility around a certain mean. Second, the MSE most easily lends itself to mathematical computations. However, given that it is a quadratic criterion, it can take into account only the information embedded in the first two moments of the distribution under analysis. In some framework, this could be considered a satisfactory approximation, if the knowledge of the mean and the variance was a sufficient condition to perfectly characterize the entire density function of the distribution. This condition holds for the Gaussian distribution. Nevertheless, this assumption cannot hold as far as most finance and economic time-series are concerned, where many time-series show a non-Gaussian behavior where skewness, leptokurtosis and higher moments play a crucial role.

Regarding the non-parametric nature of our forecasting algorithm, modelling time-series non parametrically has a long history. Robinson (1983) reviews kernel multivariate probability density and regression estimators, claiming that these methods are of particular relevance in non-gaussian time-series models, and Carbon et al. (1993) run a simulation analysis that unfolds how a non-parametric approach can compare favourably to a parametric one in the spirit of Box and Jenkins. However, in spite of the growing literature in the last years about non-parametric forecasting, there is still a big gap that needs to be filled: how to improve the forecasting accuracy of our prediction using a measure that exploits *all the information* embedded in the time-series and taking into account all the uncertainty existing in the data. To fill this gap, we make use of the entropy. Since the work of Shannon (2001), entropy has been defined as the measure describing the information content of a series of data, quantifying its randomness and uncertainty. After his seminal work, another pioneering contribution in the field can be found in Tsallis (1988).

The entropy presents several theoretical advantages with respect to the MSE. First, it depends on all the density function of the data, thus taking into account all the information stemming from the higher moments of the distribution, and not only the first two as in a gaussian environment. This directly stems from the definition of the entropy, which writes

$$H_{\alpha}(E) = \frac{1}{1-\alpha} \ln \int_E f_E^{\alpha}(\varepsilon)\, d\varepsilon \tag{3.1}$$

where $f_E$ is the density function of the forecasting error $E$, and $\alpha$ represents a free parameter. The previous definition boils down to be the particular case of the well-known Shannon entropy when the parameter $\alpha$ tends to 1 and Renyi entropy in the case $\alpha = 2$. Renyi entropy therefore simplifies to

$$H_2(E) = -\ln \int_E f_E^2(\varepsilon)\, d\varepsilon. \tag{3.2}$$

Otherwise, one can also define the differential Shannon entropy as

$$H_{DS}(E) = -\int_E f_E(\varepsilon) \ln f_E(\varepsilon)\, d\varepsilon \tag{3.3}$$

which, given the definition of the expected value as an integral, boils down to be nothing but the expectation of the loss function $-\ln f(\varepsilon)$. We can thus clearly see the difference between minimizing a loss function that is explicitly dependent on all the density function of the error instead of its square only. Moreover, to vindicate our choice of the entropy as a cost function, we provide another perspective about the effectiveness of such a loss function. When training a neural network in sample to obtain a non-parametric projection, the weights attached to the past observations projected are sequentially updated in order to decrease the expected information embedded in the error; however, since the error is defined as the observed series minus the forecast, this approach is equivalent to the maximization of the mutual information between the desired output (the observed series) and the forecast. It turns out that the algorithm progressively learns the dynamics of the target variable and takes into account all the related information.

Marques de Sa et al. (2013) is an excellent review of the properties of the entropy that can be well exploited for a more accurate forecast. In addition to shedding light on the statistical properties of the entropy, the authors present a simulation where they show how the entropy and a quadratic cost function can lead to very different results. They plot the dynamics of the continuous PDF functions belonging to the following family.

$$f(x;\alpha) = \frac{1}{4}\left[tr(x;0,\alpha) + tr(x;-\alpha,0) + tr\left(x;0,\frac{1}{\alpha}\right) + tr\left(x;-\frac{1}{\alpha},0\right)\right] \tag{3.4}$$

where $tr(x;a,b)$ is the symmetrical triangular distribution in $[a,b]$, defined for $a \geq 0$ as

$$tr(x;a,b) = \begin{cases} \frac{4\,(x-a)}{(b-a)^2}, & \text{if a} \leq x \leq \frac{a+b}{2} \\ \frac{4\,(b-x)}{(b-a)^2}, & \text{if } \frac{a+b}{2} < x \leq b \end{cases} \tag{3.5}$$

For values of $\alpha$ that converge to 0 or to $+\infty$ one obtains, progressively, longer tails.

[ Insert Figure 3.1 Near Here ]

Figure 1 shows the dynamics of the variance and the entropy of such class of densities as a function of the parameter $\alpha$. This example turns out to be very insightful because the minimum value of the variance is achieved in correspondence of $\alpha = 1$. Very interestingly, when $\alpha = 1$ on the contrary the entropy achieves almost its maximum, whereas it sharply decreases when $\alpha$ tends to 0 or to $\infty$. We can conclude that if one aims to minimize the variance (*e.g.* that of a portfolio) facing a distribution belonging to this class of density functions, he/she would prefer the case with $\alpha = 1$, this implying however to face high entropy. On the other hand, if one wishes to minimize the entropy of the distribution, the preference would go for a very different value of $\alpha$, let us say $\alpha = 0.2$, for instance, where the variance would thurn out to be very high. The preference for a class of these density functions would significantly change. In addition, the entropy would decrease remarkably for high values of $\alpha$, when the distribution becomes more fat-tailed, signalling once more that the entropy is capable to incorporate the information embedded in the higher moments, unlike the variance, which would on the contrary increase considerably in those cases.

Another example that clarifies how useful the entropy can be in forecasting is the case of the uniform distribution. Given $n$ states of the world, the worst situation for an investor when he/she has to forecast the future values of a series is that of equal probabilities across the $n$ states. In such a scenario, the investor would not be able to distinguish which of the states is more or less likely to prevail in the future. Hence, he/she would be in the case of maximum uncertainty. The density function that associates the same probability to each state is the uniform distribution, which is also well known in statistics to be the distribution with the maximum value of the entropy,indeed reflecting highest uncertainty. In settings where one of more states of the world had higher probabilities of occurrence with respect to others, the entropy would decrease, signalling less randomness and more information in the data. In this latter case, the new distribution will not be uniform anymore but may happen to have its exact same variance. Let us imagine to be in such a scenario: two distributions would present the same variance, one being uniform and the other not. According to a quadratic criterion, the two distributions would be undistinguishable, since they have the same variance, despite the lower entropy that the second distribution will have by definition. This points out how useful it can be for an investor to choose the weights in a forecasting algorithm that minimize the entropy of the error, thus exploiting at the utmost the information content of the series.

When forecasting, one can choose to either minimize *i)* the error entropy or *ii)* the *relative* entropy, *i.e.* the Kullback-Leibler divergence between the density function of the observed outcome and that of the model prediction. Both criteria are valid and admissible. However, in this paper we opt for the error entropy minimization because the Kullback-Leibler divergence involves the estimation of two density functions (realized output and predicted outcome), whereas the error entropy minimization requires the estimation of one density function only, the error density. Moreover, the distributions of the realized output and the predicted outcome may involve large values, while the entropy error is by definition the difference between these two variables, which therefore turns out to be much smaller. The estimation of a small difference between two large values is more practical and convenient than the estimation of two distributions involving large values.

The minimization of the error entropy has a very appealing property, as proven in Chen et al. (2009). For the sake of consistency with the notation used by the authors, let us define a generic cost function as $\phi(e)$ and the error criterion chosen as $\mathbb{E}\left[\phi(e)\right]$. The paper shows that there always exists a probability density function $q_\phi(e)$, such that

$q_{\phi}(e) = \exp\{-\lambda_0 - \lambda_1\phi(e)\}$, where $\lambda_0$ and $\lambda_1$ are determined by

$$\exp\{\lambda_0\} = \int_R \exp\{\lambda_1\phi(e)\}\, de \tag{3.6}$$

and

$$\mathbb{E}\left[\phi(e)\right] \exp\{\lambda_0\} = \int_R \phi(e) \exp\{\lambda_1\phi(e)\}\, de \tag{3.7}$$

such that any error criterion is equivalent to the error entropy plus the Kullback-Leibler information divergence between the probability density function of the error distribution and the density function $q_{\phi}(e)$:

$$\mathbb{E}\left[\phi(e)\right] = H(e) + D_{KL}\left(p_e(e) \mid\mid q_{\phi}(e)\right) \tag{3.8}$$

The function $q_{\phi}(e)$ is nothing but the worst case density function according to Jaynes' maximum entropy principle.

The interpretation is that any risk functional can always be rewritten as the sum of two terms: the error entropy functional plus a Kullback-Leibler divergence, which is by definition non-negative. It turns out that minimizing the error entropy is a more general and convenient error functional in that the minimization of any other error functional is nothing but the minimization of an upper bound of the error entropy $H(e)$.

Hu et al. (2013) proves the consistency of a minum error entropy approach applied to a regression problem. Since we deal with a linear projection of past observations, and we compare it to the standard OLS estimation method, the theoretical results discussed by Hu et al. (2013) fit perfectly in our setting. The paper shows three main results:

- The function that minimizes the error entropy (with a suitable constant adjustment) approximates the regression function well with confidence.
- The minimum error entropy approach is robust to the presence of outliers, in that it can still approximate well the regression function even in presence of heavy tails.

- The standard regression function $f_\rho$ is unable to minimize the information error, or, equivalently, to maximize the information potential. On the contrary, the function that minimizes the error entropy can effectively minimize the information error and be close enough to the regression function.

We start discussing the first of the three points above. The goal of any linear regression is to predict the conditional mean of the regressand $Y$ for a given regressor $X$ by estimating the regression function and its parameters:

$$f_\rho(x) = \mathbb{E}\left[Y \mid X = x\right] = \int_X y\, d\rho(y \mid x), \qquad x \in X \tag{3.9}$$

On the other hand, minimizing the error entropy can be classified as an *empirical risk minimization* (ERM) approach that aims to find the function $f_z$ that minimizes the entropy of the error distribution (we refer here to the special case of Renyi entropy where $\alpha = 2$)

$$f_z = \underset{f \in \mathcal{H}}{\operatorname{argmin}} \left\{ \log \frac{1}{n^2\, \sigma} \sum_{i=1}^{n} \sum_{j=1} nG\left( \frac{(e_i - e_j)^2}{2\sigma^2} \right) \right\} \tag{3.10}$$

We recall that the error for observation $i$ is defined as $e_i = y_i - f_i(x)$. The set $\mathcal{H}$ is called the hypothesis space for learning and its compactness ensures the existence of a minimizer $f_z$. $G(.)$ denotes the standard gaussian kernel in the Parzen windowing kernel estimation that we have applied in this paper, $\sigma$ is its bandwith and $n$ the total number of observations. Hu et al. (2013) prove the consistency of the minimum error entropy algorithm by analyzing the error function $f_z - f_\rho$ and its variance $\operatorname{var}\left[f_z - f_\rho\right]$.

**Theorem 1:**

Their consistency result states that, when $\sigma$ and $n$ are large enough, the error variance $\operatorname{var}\left[f_z - f_\rho\right]$ of the minimum error entropy algorithm can be arbitrarily close to the approximation error of the hypothesis space $\mathcal{H}$ with respect to the regression function $f_\rho$, where the approximation error of the pair $(\mathcal{H}, f_\rho)$ is defined as

$$\mathcal{D}_{\mathcal{H}} f(\rho) = \inf_{f \in \mathcal{H}} \operatorname{var}\left[f(X) - f_\rho(X)\right] \tag{3.11}$$

Very importantly, the paper proves that, under some assumptions and for any $\epsilon$ bounded between 0 and 1, it holds that

$$\operatorname{var}\left[f_z(X) - f_\rho(X)\right] = \mathcal{D}_{\mathcal{H}} f(\rho) + \epsilon \tag{3.12}$$

This result does not guarantee that $f_z$ approximates well $f_\rho$, but a constant adjustment is required, and theoretically the best constant is $\mathbb{E}\left[f_z - f_\rho\right]$, which is in practice approximated through the sample mean.

In order to deal with heavy tailed noise, the paper projects the output values onto the closed interval $[-\sqrt{m};\ \sqrt{m}]$ by the following projection

$$\pi_{\sqrt{m}}(y) = \begin{cases} y, & \text{if } y \in [-\sqrt{m};\ \sqrt{m}] \\ \sqrt{m}, & \text{if } \ y > \sqrt{m} \\ -\sqrt{m}, & \text{if } y < -\sqrt{m} \end{cases} \tag{3.13}$$

and proves the following theorem.

**Theorem 2:**

The minimum error entropy criterion is a good estimator of the regression function even in presence of big outliers, since the following relation holds

$$\left\|\hat{f}_z - f_\rho\right\|_{L^2_{\rho X}} \leq \left\| \frac{1}{m} \sum_{i=1}^{m} \left[f_z(x_i) - \pi_{\sqrt{m}}(y_i)\right] \left[f_z(X) - f_\rho(X)\right] \right\| + \sqrt{var\left(f_z(X) - f_\rho(X)\right)} \tag{3.14}$$

where the estimator of the regression function $\hat{f}_z$ can be written as

$$\hat{f}_z = f_z - \frac{1}{m} \sum_{i=1}^{m} \left[f_z(x_i) - \pi_{\sqrt{m}}(y_i)\right] \tag{3.15}$$

The punchline is that the distance between the function that minimizes the error entropy (corrected by means of the constant adjustment needed for the convergence) and the regression function is bounded from above and negligible. This holds even in presence of outliers, which makes the entropic algorithm particularly appealing since it can deal with situations where standard quadratic criteria can suffer from the presence of outliers.

The third relevant aspect discussed by the paper is that one may define different target functionals to be minimized. One can either minimize the mean square error or the entropy. The reader might therefore think that none of these criteria dominates the other and the choice might be arbitrary. The paper shows that one could choose to either make use of the function that minimizes the information error $\mathcal{E}\left[f\right]$

$$f_{\mathcal{H}} \equiv \underset{f\in\mathcal{H}}{\operatorname{argmin}}\mathcal{E}(f) = \int_z\int_z -h^2\,G\left(\frac{[(y-f(x))-(y'-f(x'))]^2}{2h^2}\right)d\rho(x,y)d\rho(x',y') \tag{3.16}$$

or the function that is the closest to the regression function

$$f_{approx} \equiv \underset{f\in\mathcal{H}}{\operatorname{argmin}} var[f(X)-f_\rho(X)] \tag{3.17}$$

The problem of a mean-square-error approach is that the regression function is not necessarily a minimizer of the information error. The novelty of the paper is to show a crucial result, explained by the following theorem.

**Theorem 3:** When the scaling parameter $h$ in the minimum error entropy approach is large enough, then $f_{\mathcal{H}}$ and $f_{approx}$ are very close, since

$$\mathcal{E}\left[f_{approx}\right] \leq \mathcal{E}\left[f_{\mathcal{H}}\right] + 2C^{''}_{\mathcal{H}}h^{-q} \tag{3.18}$$

and

$$var\left[f_{\mathcal{H}}(X)-f_\rho(X)\right] \leq var\left[f_{approx}(X)-f_\rho(X)\right] + 2C^{''}_{\mathcal{H}}h^{-q} \tag{3.19}$$

for a constant term $2C^{''}_{\mathcal{H}}h^{-q}$ (for the the full formulation we address the reader to

Hu et al. (2013)) which is negligible when $h$ is very large. Hence, the function that minimizes the mean-square error in a linear regression framework (as it applies to our paper) cannot minimize the information error, whereas the function that minimizes the error entropy does minimize the information error and is actually very close to the regression function.

Principe et al. (2002) point out another reason why the error entropy minimization should be preferrable with respect to the standard minimum mean square error approach. In the framework of adaptive systems, the authors prove that the variance of the desired response is always greater or equal to the variance of the system output. The interpretation is that, if we view the variance as a measure of uncertainty, exactly like the entropy, there is always more information in the desired variable rather than in the system output. In addition, and even more importantly, the minimum mean square error solution is the conditional mean, which is obtained by projecting the desired response on the space spanned by the input variables, with an Euclidean norm. It therefore turns out that the optimal estimator must be unbiased and, in particular, orthogonal to the error term by construction. Hence, there is no way to modify the parameters of the estimators in order to reduce the variance of the estimator further. On the contrary, the minimum error entropy method allows to train in sample the estimator in order to adjust the weights of the system progressively decreasing the entropy, *i.e.* increasing the informativeness of the estimator at each iteration of the algorithm.

Despite its appealing properties, to the best of our knowledge the entropy has never been used as a cost function for forecasting purposes. It has been widely applied in economics and finance but for very different topics. In finance, as far as the equity market is concerned, Stutzer (1996) applies the maximum entropy principle to estimate risk-neutral (equivalent martingale) probabilities that correctly price the primary assets, as well as any pre-designated subset of derivative securities. With regard to the option market, also Buchen et al. (1996) makes use of the maximum entropy principle but to show how to recover the probability distribution of an asset, given an expectation pricing model and a set of option prices at different strikes. Stutzer (2000) shows how to generalize the Black-Scholes option pricing model by means of the entropy, taking into account the impact of non-normal stock returns.

Regarding the bond market, Brody et al. (2002) uses the maximum entropy principle to develop a new calibration methodology of the term structure. As to the banking sector, Mistrulli (2011) applies the maximum entropy principle to study how contagion propagates within the interbank market after a liquidity shock occurred to a bank. Moreover, Backus et al. (2014) applies the entropy to generalize the famous Hansen-Jagannathan (2001)'s bound, shedding light on the desirable properties that the entropy has when dealing with asset pricing models, as for example the fact that *"it incorporates non-normal components of the pricing kernel and returns in a particularly simple and transparent way"*.

In utility theory, Frittelli (2006) provides evidence of the existence of a unique equivalent martingale measure that minimizes the relative entropy, with respect to the physical probability measure, suggesting the equivalence between the maximization of the expected exponential utility and the minimization of the relative entropy. In econometrics, Kitamura et al. (1997) applies the Kullback-Leibler divergence to define an information-theoretic alternative to GMM, providing evidence of a very good performance with small samples, where traditional GMM may have problems. Several papers have applied the entropy and its desirable properties in the broad field of economics. To cite only a few of them, entropy has attracted the attention of economists since Daly (1968) and Daly (1974), who links the entropy with his theory of the steady-state and the evolutionary process of the economy, passing through Berry et al. (1979), who uses the entropy to measure the connection between diversification and corporate growth in the field of industrial economy, up until Fisk (2011), elaborating his discourse to prove that *"entropy really counts in economics"*.

Bradley et al. (2004) also go further and model stock returns and industrial production as non-linear and state dependent, with dynamics linked to the sign and magnitude of the past realization of returns and the growth of industrial production. The authors conduct an out-of-sample forecasting exercise and compare the forecasting performance of various non-linear models with that of a linear one. Regarding stock returns, they find that the linear model generally does as well or better than any of the non-linear models, while as far as the growth in industrial production is concerned, two of the non-linear models outperformed the linear model, unlike all the other non-linear estimators. The same issue is also raised and discussed by Dacco et al. (1999), who underscore that most non-linear techniques give good in-sample fit but poor out-of sample performance. Interestingly, the paper discusses the limitations to the use of the Markov switching models for forecasting.

As far Markov models are concerned, they have also been extensively applied to many different economic and financial time-series. Turner et al. (1989) proposes to model stock market excess returns with a two-state Markov model, where the states account for high and low market variance. Always with reference to the stock market, Hamilton et al. (1994) models stock returns by means of low-, moderate-, and high-volatility regimes. It attributes most of the persistence in stock price volatility to the persistence of these low-, moderate-, and high-volatility regimes, which typically last for several years, and where the high-volatility regime is to some degree associated with economic recessions. Moreover, the paper claims that the fundamental innovations are much better described as coming from a Student t-distribution with low degrees of freedom than from a normal distribution, which therefore postulates the need of a non-Gaussian forecasting model as our entropic algorithm.

The examples brought about by these two papers corroborate our aforementioned point: One can always *arbitrarily* choose a particular model to fit and thanks to which they can move to forecast the future values of a time-series, according to some economic assumptions. These two papers have chosen two different specifications for the Markov switching model, the former opting for a two-state Markov process and the latter for a three-state one. This has crucial implications for forecasting, since the prediction hinges on the kind of model that has been chosen to fit the data. Once more, a non-parametric forecasting algorithm able to capture *all* the information embedded in *all* the moments of the observed time-series would turn out to be a much easier tool to be applied and would ensure to maximize the information content of the time-series of interest. Also, its performance would not depend on any *a-priori* assumptions, neither more or less plausible, nor more or less universally valid and verifiable.

GDP and stock returns have not been the only variables modelled by means of Markov switching models. Dueker and Neely (2007) show how to effectively apply a Markov switching model to implement trading strategies on exchange rates. Alexander et al. (2007) also claims the relevance of Markov-switching models but applied to the CDS market, highlighting that single-regime models are unable to separate turbulent periods for normal ones and this leads to underestimate equity hedge-ratios during volatile periods. Credit ratings have also been studied applying Markov switching models: Among others, Klaassen et al. (2006), who analyze portfolio credit risk, and Bangia et al.(2002), who condition the migration matrix from the state of recession to that of expansion, and *vice versa*, to some financial information which are claimed to decisively affect financial distress and the default probability.

## 3.3 The model

We apply a linear estimator that minimizes the entropy of the forecasting error distribution. We assume to have at our disposal a time-series with $N + k$ observations. Our forecast of the value of the process at any generic time $t$ takes the form of a linear projection of all previous $k$ observations from $t - 1$ up to $t - k$.

We denote by $Y$ the random variable defining our target to be estimated. Its realization at time $t$ is denoted by $y_t$ and its values at any $t$ are collected in the vector $\boldsymbol{y}_{N\times1}$. Defining our estimator by the random variable $\hat{Y}$, the realizations of which, at any point in time, being collected in the vector $\hat{\boldsymbol{y}}_{N\times1}$, the forecasting error turns out to be $E = Y - \hat{Y}$, characterized by the density function $f_E(\varepsilon)$. The vector containing all its realizations at any time is labelled as $\boldsymbol{\varepsilon}_{N\times1}$. We denote as $\boldsymbol{\beta}_{k\times1}$ the vector of weights attached to the past $k$ observations used for the prediction.

We train our forecasting algorithm in sample to find the vector $\boldsymbol{\beta}_{k\times1}$ that minimizes the entropy of the forecasting error distribution. The prediction errors in sample are collected in the vector

$$\boldsymbol{\varepsilon}_{N\times1} = \boldsymbol{y}_{N\times1} - \hat{\boldsymbol{y}}_{N\times1} \tag{3.20}$$

where the vector collecting the target values to be estimated at each point in time is

$$\boldsymbol{y}_{N\times 1} = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-N+1} \end{bmatrix}$$

and, collecting all the past observations used in the linear projections for each point forecast in the matrix $\boldsymbol{X}_{N\times k}$, our linear forecast at any point in time therefore writes

$$\hat{\boldsymbol{y}}_{N\times 1} \equiv \boldsymbol{X}_{N\times k}\,\boldsymbol{\beta}_{k\times 1} = \begin{bmatrix} y_{t-1} & y_{t-2} & \cdots & y_{t-k} \\ y_{t-2} & y_{t-3} & \cdots & y_{t-k-1} \\ \vdots & \vdots & \ddots & \vdots \\ y_{t-N} & y_{t-N-1} & \cdots & y_{t-N-k} \end{bmatrix}_{N\times k} \cdot \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix}_{k\times 1} \tag{3.21}$$

We aim to minimize the entropy of order $\alpha$ of the error distribution, denoted as $H_\alpha(E)$, conditional on the estimator being a linear function of the past $k$ observations in time, such that our optimization problem writes

$$\underset{\beta}{\operatorname{argmin}}\, H_\alpha(E) = \frac{1}{1-\alpha}\log \int_E f_E^\alpha(\varepsilon)d\varepsilon$$

$$s.t.: E = Y - \hat{Y} = Y - X\,\beta$$

We apply a numerical first-order optimization algorithm called steepest descent, see for instance Arfken (1985). This iterative procedure is repeated $m = 1, 2, ..., M$ times until a stopping condition is achieved. Step by step we aim to get closer and closer to the global minimum of the entropy by moving along the direction given by the negative of its gradient, since we are searching a minimum. We stop when the gradient is sufficiently close to a zero vector. Our numerical optimization is based on the following steps.

- **Step 1**: To start the algorithm, we set $\boldsymbol{\beta}^{(1)}_{k\times 1} = \boldsymbol{\beta}^{MSE}_{k\times 1}$, where $\boldsymbol{\beta}^{MSE}_{k\times 1}$ is the vector of weights that minimizes the mean square error in our sample, which boils down to be the standard well-known OLS estimator:

$$\boldsymbol{\beta}_{k\times1}^{MSE} = \left[\boldsymbol{X}_{N\times k}^{T} \cdot \boldsymbol{X}_{N\times k}\right]^{-1} \cdot \left[\boldsymbol{X}_{N\times k}^{T} \cdot \boldsymbol{y}_{N\times1}\right] \tag{3.22}$$

The rationale is that the vector that yields the global minimum of the MSE should not be reasonably too far from the global minimum of the entropy. Nevertheless, we also run the same search from 100 different random starting points, in order to evaluate whether the point from which we start the algorithm may lead to the convergence to a different minimum. In all our simulations and empirical analysis, the algorithm always converges to the same final vector that is obtained when starting from $\boldsymbol{\beta}_{k\times1}^{MSE}$. From now onwards, we iterate $m = 1, 2, ..., M$ times steps 2 to 4 until the stopping condition is met.

- **Step 2**: In order to find the vector of weights that minimizes the entropy, we compute the gradient $\frac{\partial H_\alpha(E)}{\partial \boldsymbol{\beta_{k\times1}}}$.

- **Step 3**: We adjust the vector of weights by adopting a learning rate $\eta^{(m)}$ that scales the gradient in order to ensure smooth convergence. We sum the negative of the gradient since we point in the direction to find a global minimum.

$$\boldsymbol{\beta}_{k\times1}^{(m+1)} = \boldsymbol{\beta}_{k\times1}^{(m)} - \eta^{(m)} \left.\frac{\partial H_\alpha(E)}{\partial \boldsymbol{\beta}_{k\times1}}\right|_{\boldsymbol{\beta}_{k\times1}=\boldsymbol{\beta}_{k\times1}^{(m)}} \tag{3.23}$$

It is worthwhile underscoring that $\eta^{(m)}$ is calibrated to ensure convergence by decreasing at each iteration. Both in our simulations and our empirical analysis, we calibrate $\eta^{(m)}$ in such a way that it ensures that smooth convergence is achieved with only 36 iterations.

- **Step 4**: We stop the algorithm if the following stopping condition is met:

$$\sqrt{\left(\left.\frac{\partial H_\alpha(E)}{\partial \beta_1}\right|_{\beta_1=\beta_1^{(m)}}\right)^2 + \left(\left.\frac{\partial H_\alpha(E)}{\partial \beta_2}\right|_{\beta_2=\beta_2^{(m)}}\right)^2 + ... + \left(\left.\frac{\partial H_\alpha(E)}{\partial \beta_k}\right|_{\beta_k=\beta_k^{(m)}}\right)^2} \leq 10^{-3} \tag{3.24}$$

otherwise we go back to step 2.

The entropy is a function that can have multiple minima. Therefore, we cannot neglect the probability that our search algorithm will find two or more different points attaining the same minimum entropy level. In such a situation, we proceed by selecting, among those points, the one that yields the lowest forecasting mean square error, which will be unique by definition.

In order to estimate in sample the entropy, we first recall that for any random variable $X$, characterized by a density function $f_X(x)$, its expected value writes

$$\mathbb{E}[X] = \int_X x\, f_X(x)\, dx \tag{3.25}$$

and that Renyi entropy of order $\alpha$ of the forecasting error $E$ writes

$$H_\alpha(E) = \frac{1}{1-\alpha} \log \int_E f_E(\varepsilon)^\alpha \, d\varepsilon \tag{3.26}$$

such that, in equation (3.26) we can replace the integral with the expectation operator, which yields

$$H_\alpha(E) = \frac{1}{1-\alpha} \log \mathbb{E}\left[f_E(\varepsilon)^{\alpha-1}\right] \tag{3.27}$$

To estimate the error entropy in sample, we *i)* replace the expectation operator with its sample counterpart, and *ii)* estimate the density function by means of a kernel estimation (Parzen windowing, see Parzen (1962) for more details). Operationally, this estimation technique works as follows.

If we wish to estimate the value of the density function at a point $\xi$, we place a window function with bandwidth $\sigma$ at $\xi$ and determine what is the contribution of each observation $\varepsilon_i$ to this window. The estimated PDF value $\hat{f}_E(\xi)$ is then the average of the total contributions from each forecasting error $\varepsilon_i$, with $i = 1, 2, ..., N$.

$$\hat{f}_E(\xi) = \frac{1}{N} \sum_{i=t-N+1}^{t} \kappa_\sigma \left(\xi - \varepsilon_i\right) \tag{3.28}$$

Regarding the choice of the kernel bandwith $\sigma$, there is a trade-off between precision of the estimation and convergence. When $\sigma$ is too large, the algorithm can converge faster but too many observations fall in the same region and are classified equally, despite the fact that there may be large heterogeneity in their values. On the other hand, when $\sigma$ is very small, the estimation is very accurate but achieving convergence numerically might be difficult. Following Silverman (1986), we choose a fixed value for the bandwidth equal to

$$\sigma = \sigma_r \, \frac{4\,(N+k)}{3}^{\frac{1}{5}}, \tag{3.29}$$

where $\sigma_r$ denotes the in-sample standard deviation of the time-series of interest. This choice turns out to be indeed beneficial because the algorithm converges quickly and estimates precisely the density function. We then employ a Gaussian kernel

$$\kappa_\sigma(\xi - \varepsilon) = \frac{1}{\sqrt{2\,\pi\,\sigma^2}}\, e^{-\frac{1}{2\,\sigma^2}\,(\xi-\varepsilon)^2} \tag{3.30}$$

thus the entropy estimated from the sample writes

$$\hat{H}_\alpha(E) = \frac{1}{1-\alpha}\, \log \frac{1}{N} \sum_{j=t-N+1}^{t} \left( \frac{1}{N} \sum_{i=t-N+1}^{t} \kappa_\sigma(\varepsilon_j - \varepsilon_i) \right)^{\alpha-1} \tag{3.31}$$

where the inner summation refers to the kernel estimation of the density function, while the outer sum is related to the replacement of the expectation operator with the sample mean. Straightforwardly, since $N \cdot N^{\alpha-1} = N^\alpha$, the estimated entropy can then be expressed as

$$\hat{H}_\alpha(E) = \frac{1}{1-\alpha}\, \log \frac{1}{N^\alpha} \sum_{j=t-N+1}^{t} \left( \sum_{i=t-N+1}^{t} \kappa_\sigma(\varepsilon_j - \varepsilon_i) \right)^{\alpha-1} \tag{3.32}$$

The expression inside the logarithm is called *information potential*, that we denote as $\hat{V}_\alpha(E)$ and that therefore writes

$$\hat{V}_\alpha(E) = \frac{1}{N^\alpha} \sum_{j=t-N+1}^{t} \left( \sum_{i=t-N+1}^{t} \kappa_\sigma(\varepsilon_j - \varepsilon_i) \right)^{\alpha-1} \tag{3.33}$$

Given that the following relationship between the entropy and the information potential always holds by construction,

$$H_\alpha(E) = \frac{1}{1-\alpha} \log\left[V_\alpha(E)\right] \tag{3.34}$$

when considering the cases $\alpha > 1$ the minimization of the entropy yields the same result as the maximization of the information potential. Accordingly, we derive $V_\alpha(E)$ and employ it in equation (3.23), changing the sign from minus to plus since we are now searching a maximum and not a minimum anymore. From this result, one could also easily adjust the final formula to derive the gradient to be applied to minimize the entropy, which would yield the same result.

We recall that the forecasting error at time $t$ can be defined as

$$\varepsilon_t = y_t - \hat{y}_t = y_t - \begin{bmatrix} \beta_1 & \beta_2 & \cdots & \beta_k \end{bmatrix}_{1\times k} \cdot \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-k} \end{bmatrix}_{k\times 1} \tag{3.35}$$

For the sake of clearness, let us define the vector of inputs for a generic point in time $\tau$ as

$$\boldsymbol{x}_{k\times 1}^{(\tau)} \equiv \begin{bmatrix} y_{\tau-1} \\ y_{\tau-2} \\ \vdots \\ y_{\tau-k} \end{bmatrix}_{k\times 1} \tag{3.36}$$

such that we can write the forecasting error at any time $\tau$ in a more compact form

$$\varepsilon_\tau = y_\tau - \hat{y}_\tau = y_\tau - \boldsymbol{\beta}_{k\times 1}^T \cdot \boldsymbol{x}_{k\times 1}^{(\tau)}, \qquad \tau = t-N+1, ..., t \tag{3.37}$$

To compute $\frac{\partial V_\alpha(E)}{\partial \boldsymbol{\beta}_{k\times 1}}$ we need to take the first derivative of an exponential function because the kernel is assumed to be Gaussian. However, the argument of the kernel is the difference between two forecasting errors at different points in time.

$$\varepsilon_j - \varepsilon_i = y_j - y_\tau - \boldsymbol{\beta}_{k\times 1}^T \cdot \boldsymbol{x}_{k\times 1}^{(j)} - \left( y_i - y_\tau - \boldsymbol{\beta}_{k\times 1}^T \cdot \boldsymbol{x}_{k\times 1}^{(i)} \right) \tag{3.38}$$

It turns out that our entropic functional incorporates an exponential function whose exponent is itself a function of $\boldsymbol{\beta}_{k\times 1}$, the variable with respect to which we are taking the derivative. Hence, we need to apply the chain rule, which in general form writes

$$\frac{\partial G\left[f(x)\right]}{\partial x} = \frac{\partial G\left[f(x)\right]}{\partial f(x)} \cdot \frac{\partial f(x)}{\partial x} \tag{3.39}$$

In our case, the first part of the chain rule is nothing but the derivative of the information potential with respect to the Gaussian kernel, and the second term refers to the derivative of the gaussian kernel with respect to the vector of weights. In that respect, from equation (3.38) we obtain that the derivative of the argument of the exponent writes

$$\frac{\partial(\varepsilon_j - \varepsilon_i)}{\partial \boldsymbol{\beta}_{k\times 1}} = \boldsymbol{x}_{k\times 1}^{(i)} - \boldsymbol{x}_{k\times 1}^{(j)} \tag{3.40}$$

and accordingly, the derivative of the information potential is

$$\frac{\partial V_\alpha(E)}{\partial \boldsymbol{\beta}_{k\times 1}} = \frac{\alpha-1}{N^\alpha} \sum_{j=t-N+1}^{t} \left( \sum_{i=t-N+1}^{t} \kappa_\sigma(\varepsilon_j - \varepsilon_i) \right)^{\alpha-2} \left( \sum_{i=t-N+1}^{t} \kappa_\sigma^{'}(\varepsilon_j - \varepsilon_i) \left( \boldsymbol{x}_{k\times 1}^{(i)} - \boldsymbol{x}_{k\times 1}^{(j)} \right) \right) \tag{3.41}$$

from which

$$\begin{gathered} \frac{\partial V_\alpha(E)}{\partial \boldsymbol{\beta}_{\boldsymbol{k\times 1}}} = \frac{\alpha-1}{N^\alpha} \sum_{j=t-N+1}^{t} \left( \sum_{i=t-N+1}^{t} \frac{1}{\sqrt{2\,\pi\,\sigma^2}}\, e^{-\frac{1}{2\sigma^2}(\varepsilon_j-\varepsilon_i)^2} \right)^{\alpha-2} \\ \left( \sum_{i=t-N+1}^{t} -\frac{1}{\sigma^2}\,(\varepsilon_j - \varepsilon_i)\, \frac{1}{\sqrt{2\,\pi\,\sigma^2}}\, e^{-\frac{1}{2\sigma^2}(\varepsilon_j-\varepsilon_i)^2} \left( \boldsymbol{x}_{k\times 1}^{(i)} - \boldsymbol{x}_{k\times 1}^{(j)} \right) \right) \end{gathered} \tag{3.42}$$

and rearranging

$$\frac{\partial V_\alpha(E)}{\partial \boldsymbol{\beta_{k\times 1}}} = \frac{\alpha-1}{N^\alpha} \sum_{j=t-N+1}^{t} \left( \sum_{i=t-N+1}^{t} \frac{1}{\sqrt{2\,\pi\,\sigma^2}}\, e^{-\frac{1}{2\sigma^2}(\varepsilon_j-\varepsilon_i)^2} \right)^{\alpha-2}$$
$$\left( \sum_{i=t-N+1}^{t} \frac{(\varepsilon_j-\varepsilon_i)}{\sqrt{2\pi}\,\sigma^3}\, e^{-\frac{1}{\sqrt{2\pi\sigma^2}}(e_j-e_i)^2} \left( \boldsymbol{x}_{k\times 1}^{(j)} - \boldsymbol{x}_{k\times 1}^{(i)} \right) \right) \tag{3.43}$$

Given the relationship between the entropy and the information potential shown above, it then suffices to recall that

$$\frac{\partial log\,(f(x))}{\partial x} = \frac{f^{'}(x)}{f(x)} \tag{3.44}$$

if one wanted to straightforwardly obtain the final formula for the gradient of the entropy $\frac{\partial H_\alpha(E)}{\partial \boldsymbol{\beta}_{k\times 1}}$.

## 3.4 Simulation results: stochastic dominance

In this section we compare the performance of our entropic algorithm with that of the quadratic estimator on simulated stochastic processes. We aim to establish a stochastic dominance argument for our entropic technique with respect the quadratic criterion. For this purpose, we first test our algorithm in a framework that is well known to be optimal for a quadratic estimator. We simulate a linear process with Gaussian innovations and without any switching dynamics. We assume that the forecaster knows the form of the stochastic process, therefore being in the case of correct model specification. In such a scenario, we show that our entropic algorithm attains the same performance with respect to the quadratic estimator.

We then move to assess the predictive accuracy when progressively departing from a linear and gaussian setting. To start with, we present the results for a linear autoregressive process with CGMY innovations and a two-state Markov switch. Afterwards, we further depart from the base scenario by introducing a process that still presents non-gaussian and switching dynamics but to which we add other non-linearities. We show that the entropy-based technique progressively increases its outperformance with respect to the quadratic estimator as we depart farther away from a linear and Gaussian setting.

We evaluate the performance of the forecasting algorithms on two different yet related set of indicators. First, we analyze the accuracy of the predictions from a purely *statistical* point of view. We focus on the forecasting error distribution for the entropic and quadratic criteria, out of sample. We compare the first 4 moments as well as the first 20 central moments of these two distributions. Ideally, a flawless forecasting algorithm would produce an error distribution that would lool like a Dirac-$\delta$ centered at the origin. Hence, the best performance between the two algorithms is achieved by the one displaying moments that are closer to zero. In addition, we present the full empirical distribution function of the forecasting errors out of sample, which, ideally, should be as concentrated as possible around zero.

Second, we test the performance of the algorithms on a set of purely *financial* indicators. We assume that our simulated series represents daily changes in the prices of a fictitious asset. Accordingly, the forecasted value of our algorithm tells us the prediction in the daily change of the asset price. We build a trading strategy that aims to exploit the signals of the forecasting algorithm. We start with a basic strategy where we buy one quantity of the asset if the predicted increment is positive, whereas we short-sell one quantity if the predicted increment is negative. The strategy can be easily modified to make it more sophisticated by changing the quantities bought or sold short according to the intensity of the signal stemming from the predicted change. A higher predicted change would be associated with higher quantities bought or sold short. We assume to close the position at the end of the day and re-open it according to the new signal the day after. In this way, the basic strategy can only have quantities bought or sold short equal to $+1$ or $-1$.

We end up having at our disposal a time-series of returns for the trading strategy associated with the entropic algorithm and a time-series of returns based on the quadratic forecast. We compute and compare the annualized Sharpe ratios of the two strategies. In addition, we aim to make sure that the best algorithm does not suffer from any large and unexpected negative returns due to the fact that it could produce, even only very rarely, completely wrong signals able to strongly affect the portfolio of the investor. For this purpose, we also compute the Sterling ratio, which is defined as the final cumulated value of the portfolio (minus the amount invested at the beginning of the first period, assumed to be 1$) scaled by the absolute value of the largest negative daily return experienced by the strategy. The Sterling ratio thus penalizes more those strategies that may well produce higher returns and lower volatility, but which could also suffer more from some extreme negative events.

In the set of our financial indicators we also include what we call ”Hit ratio” and ”Extended hit ratio”. The former indicates how many times the algorithm correctly predicts the *direction* of the asset price, in that it correctly forecasts a positive increment when the price of the asset indeed increases, and *vice versa*. We present this result for both algorithms in order to compare the percentage of correct predictions of the direction of the price change. The latter is an indicator that turns out to be most useful to identify whether the largest forecasting errors can nevertheless be considered useful and not dangerous for an investor.

The following example clarifies this issue. Let us assume that asset A has a price of 10$ at time $t$ and it turns out to have a price of 10.1$ in $t+1$. Let us also assume that the estimator predicts a positive and remarkable price increment from $t$ to $t+1$ equal to +50%, therefore predicting that the price of asset A will move from 10$ to 15$. The prediction error would be huge, with a predicted +50% against an actual variation of +1%. Nevertheless, the investor would open a long position on the asset since the predicted change is positive, and would make a profit accordingly. If the estimator has a very large forecasting error, it can however be a source of profits for the investor under the condition that it predicts correctly the direction of the price change. In such a scenario, the investor would open a long (short) position when the algorithm predicts an increase (a decrease) in the price of the asset, and he/she would anyway gain a profit despite the large forecasting error.

The computation of the ”Extended hit ratio” works as follows. We look in the tails of the forecasting error distributions and isolate the largest positive and negative values. For instance, we analyze those values that are larger than the 99th percentile and lower than the 1st percentile. We check how many times it happens that these large errors were associated with the correct or wrong sign of the price change. If most of the times the large errors are nevertheless associated with correct predictions of this sign, then these outliers can be considered as "good" outliers for an investor. On the contrary, when the algorithm signals the wrong sign of the price change, these errors can be very dangerous for the strategy portfolio, in particular if the investor decides to calibrate the quantities to buy or short sell according to the strength of the signal. To take all this into account, we report the results for the extended hit ratio for different values of the percentiles of the forecasting error distribution out of sample.

### 3.4.1 Gaussian and linear process under correct model specification

We first investigate the performance of the two forecasting algorithms in a perfectly Gaussian and linear setting. We simulate the following stochastic process

$$r_t = 0.3\, r_{t-1} - 0.5\, r_{t-2} + 0.7\, r_{t-3} + \varepsilon_t, \qquad \varepsilon \sim \mathcal{N}\left(\mu, \sigma^2\right) \tag{3.45}$$

and we assume to be under correct model specification, in that the forecaster is able to identify that the stochastic process underlying our time-series of interest is indeed an AR(3) with Gaussian innovations. We are interested in the one-step ahead forecast.

We train our entropic algorithm on a sample comprising 6,000 observations. Then, we assess and compare the performance of the two algorithms out of sample on a set of 3,000 observations. Since we assume to know precisely the form of the stochastic process generating the observed data, our forecast turns out to be a linear projection of, precisely, the last 3 observations in time. Concerning the quadratic algorithm, this conceptually boils down to fit in sample an AR(3) process to the data, estimating the parameters via OLS and then use this model to forecast out of sample. On the set of 6,000 observations, we compute the weights $\phi_1$, $\phi_2$ and $\phi_3$ attached to the 3 past observations to be linearly projected. For the sake of simplicity, we assume to keep these parameters fixed out of sample, hence our one-step-ahead forecast is always made with the same parameters.

Hence, conditional on being at time $t$, we project the observations in $t$, $t-1$ and $t-2$ to obtain our forecast of the value of the process in $t+1$ as

$$\mathbb{E}\left[y_{t+1} \mid \mathcal{F}_t\right] = \hat{\phi}_1\, y_t + \hat{\phi}_2\, y_{t-1} + \hat{\phi}_3\, y_{t-2} \tag{3.46}$$

The related forecasting error at time $t+1$ would write

$$\varepsilon_{t+1} = y_{t+1} - \mathbb{E}\left[y_{t+1} \mid \mathcal{F}_t\right] \tag{3.47}$$

We end up having at our disposal a time-series of 3,000 one-step-ahead forecasting errors for the quadratic and the entropic algorithms, that we compare. Figure 2 plots the empirical density functions of these out-of-sample forecasting errors.

[ Insert Figure 3.2 Near Here ]

The two distributions almost perfectly coincide one with each other. The entropic forecast attains the same level of forecasting precision out of sample, despite the fact that we are in a linear and Gaussian setting under correct model specification. In order to check further the validity of this result, Tables 3.1 and 3.2 report, respectively, the first 4 non-central and first 20 central moments of the forecasting errors distributions.

[ Insert Tables 3.1 and 3.2 Near Here ]

These two tables confirm the interpretation that stems from the two forecasting errors distributions: all the moments, even the highest ones, are statistically identical. The entropy never produces higher moments of the error distribution with respect to the quadratic estimator, hence attaining the same level of prediction accuracy.

In addition, the Sharpe ratio and the Sterling ratio for both algorithms are also the same: the annualized Sharpe ratio is 10 and the Sterling ratio is 385 for both strategies. Their high values are not surprising: Assuming the stochastic process generating the data is known, with a distribution that is neither skewed nor leptokurtic, both estimators correctly guess the sign of the price change almost everytime. These results are striking.

The entropic algorithm manages to attain the same level of forecasting accuracy as the quadratic one in such a Gaussian and linear setting. This is remarkably relevant in that the conditional mean is known to be the estimator that minimizes the MSE, with the latter being an optimal cost-function if the data generating process is Gaussian. Given that we also assume correct model specification, it is mathematically impossible to beat the conditional mean is such a framework. Therefore, the result achieved by the entropy is remarkable and of considerable interest, since its performance is no different than that of the quadratic estimator.

### 3.4.2 Non-Gaussian and non-linear process with Markov switches under model mis-specification

We now move to introduce some non-linearities in the DGP. We simulate the following two-state Markov process

$$r_t = \begin{cases} 0.1\, r_{t-1} + 0.6\, r_{t-2} - 0.2\, r_{t-3} + u_t, & \text{if S=1} \\ 0.3\, r_{t-1} + 0.2\, r_{t-2} - 0.7\, r_{t-3} + v_t, & \text{if S=2} \end{cases} \tag{3.48}$$

where both $u_t$ and $v_t$ are distributed as a CGMY(5,8,16,0.8) and the transition matrix defining the probabilities to be in state $S = 1$ or in state $S = 2$ is

$$M = \begin{bmatrix} 0.7 & 0.3 \\ 0.6 & 0.4 \end{bmatrix}$$

We assume to be under (partial) model mis-specification: the forecaster correctly identifies some dependences of the process at a certain time $t$ on the past 3 observations. Nevertheless, he/she postulates the existence of an underlying AR(3) process, not identifying the switching dynamics. We therefore proceed as in the previous case, with a linear projection of the last 3 observations, which boils down to be again a standard OLS approach when the cost function is the MSE. This example sheds light on what degree of lack of precision would stem from correctly fitting an AR(3) process to the data but without taking into account the presence of a Markov switch.

Table 3.3 reports the values of the entropy and the information potential attained in sample by the two algorithms.

[ Insert Table 3.3 Near Here ]

It is apparent that the MSE-based technique achieves a much lower value of the information potential, thus a higher value of the entropy. This unfolds that the making use of a vector of weights that minimizes the entropy can be beneficial in that there is still information that can be extrapolated from the time-series and that a quadratic algorithm is not able to take into account.

[ Insert Figure 3.3 Near Here ]

Figure 3 reports the empirical distribution of the forecasting errors out of sample. The entropic algorithm produces a density of the error which is much more concentrated around zero, and the difference between the two distributions is remarkable. This is the most relevant result of this simulation: when we introduce Markov-switching dynamics that are neglected by the forecaster, the entropy produces a much more accurate forecast that shrinks the errors distribution towards zero.

Table 3.4 shows the first 20 central moments of the true distribution of the series of interest out of sample as well as the corresponding predictions obtained through the quadratic and the entropic algorithm.

[ Insert Table 3.4 Near Here ]

Table 3.4 confirms the insight that we could learn from Figure 3: the entropic algorithm strongly outperforms the MSE-based approach in that it matches much better the observed true distribution. This striking matching corroborates and is consistent with the result displayed by the empirical density functions of the error. A closer look into Table 3.4 indeed shows that the order of magnitude of the central moments of the observed time-series is almost always the same as that of the entropy predictions but very far from that of the MSE predictions. The results holds up to the 20th central moment and the distance between the MSE and the entropy gets larger and larger as we look at the higher moments, as expected. For example, the order of magnitude of the 20th central moment is $-8$ for the observed time-series as well as the entropy prediction, whereas it is $-17$ for the MSE.

In Tables 3.5 and 3.6 we report the first 4 moments of the forecasting errors out of sample and the first 20 central moments of the errors.

[ Insert Tables 3.5 and 3.6 Near Here ]

In our analysis, we find very few outliers produced by the entropic technique that could potentially lead to a misleading conclusion. Because of these few outliers, the difference in the moments of the error distribution would appear much lower than what actually is and than what it stems from the results plotted in Figure 3. Therefore, we proceed as follows. First, we delete those values of the forecasting errors that are higher than the 99th percentile and lower than the 1st percentile for the entropic criterion. Results are displayed in Tables 3.5 and 3.6. Second, we check if these outliers can be considered "good" or "bad" for an investor, computing our "extended hit ratio".

We can clearly notice the strong outperformance of the entropic algorithm, which displays much lower moments. In order to check for the robustness of the results, we compute and present the hit ratio and the extended hit ratio, as well as the fraction of outliers for the entropic algorithm that nevertheless correctly predict the sign of the future price change. Tables 3.7 and 3.8 report these results.

[ Insert Table 3.7 Near Here ]

Table 3.7 shows that 100% of outliers are associated with a correct prediction of the sign of the price change as far as the first and last percentiles are concerned. An investigation farther from the deep tail unfolds that 99.3% of the outliers lying below the 5th percentile and above the 95th percentile correctly estimate the direction of the price change. In the same fashion, this message is reinforced by focusing on the observations below the 10th and above the 90th percentiles, where 98% of the observations are ”good” outliers for an investor. The main message is therefore very clear: Even in the tails, where the forecasting errors are largest, the entropic algorithm predicts the right sign of the price change, allowing the investor to design a strategy that turns out to be profitable also in these cases.

The same information is conveyed by the hit ratio and the extended hit ratio. presented in Table 3.8.

[ Insert Table 3.8 Near Here ]

Despite the fact that the fractions of correct predictions of the sign of the price change are not very different, slightly in favor of the entropic algorithm, the extended hit ratio of the entropic method is much higher, 29% against 6%. This means that the entropic algorithm overshoots more often the prediction, still guessing correctly the direction of the price change, many more times than the quadratic method. This has relevant and positive implications for an investor because the latter could potentially increase the quantities to be bought or sold short according to the strength of such trading signals, leveraging the returns.

Last but not least, we provide the reader with the results of an investment strategy that hinges on the forecasting signals produced by the two algorithms. The investor can even design an aggressive trading strategy where the weights are not anymore $+1$ or $-1$ but they become a function of the predicted increment. The rationale is that the stronger the forecasting signal is, the more aggressive the trading strategy should be. It is reasonable to assume that a trader may be more willing to leverage his/her positions when the algorithm predicts a stronger signal. For instance, if the predicted increment of the price of the asset were +5%, the investor would reasonably leverage more the positions with respect to the case when the predicted price change is only +0.1%. As an example, we tested an aggressive trading strategy where the weights are defined as the predicted price change multiplied by $2,000$. This very aggressive strategy would produce a Sharpe ratio of 18.65 for the entropy versus 4.09 for the MSE, presenting also a much higher Sterling ratio. This sheds light on how an investor could benefit from these forecasting signals, being able to design not only prudential strategies but also aggressive ones.

### 3.4.3 Non-Gaussian process with non-linear form and Markov switches under model mis-specification

We now present a third simulation where we depart even more from a Gaussian and linear environment. We simulate $9,000$ observations generated by the following stochastic process

$$r_t = \begin{cases} 0.5\, r_{t-1} + 0.4\, r_{t-2} + 0.2\, r_{t-1}\, r_{t-2} - 0.8\, r_{t-2}\, r_{t-3} + u_t, & u \sim CGMY(5, 8, 16, 0.8), \quad \text{if S=1} \\ -0.6\, r_{t-1} - 0.5\, r_{t-2} + 0.8\, r_{t-1}\, r_{t-2} - 0.3\, r_{t-2}\, r_{t-3} + v_t, & v \sim CGMY(5, 8, 16, 0.8), \quad \text{if S=2} \end{cases} \tag{3.49}$$

where the transition matrix defining the probabilities to be in state $S = 1$ or state $S = 2$ is

$$M = \begin{bmatrix} 0.8 & 0.2 \\ 0.6 & 0.4 \end{bmatrix}$$

We assume to be under (complete) model mis-specification: the forecaster cannot identify the distribution of the underlying stochastic process. The form of the process is non-linear, there are switching dynamics between two states and the coefficients of the process vary significantly between one state and the other. With respect to the previous simulation, additional complexity is also added by the values that are assigned to the coefficients of the autoregressive processes: unlike the previous case, where these coefficients only displayed limited variation, here we impose a much larger variation in the values of the coefficients across the different states. They also frequently switch sign. For example, in state 1, the parameter attached to the observation at time $t-1$ has value 0.5, switching to $-0.6$ in state 2. We aim to evaluate how the different algorithms deal with all this complexity.

We consider a forecaster who cannot identify precisely the high non-linearities in the data and who therefore linearly projects the past $k$ observations in time. In this subsection, we will test the results for several different values of $k$, to investigate whether including more and more lags penalizes either or both of the two algorithms. The rationale is that including more lags in the linear projection should help incorporate more information, but on the other hand it could also lead to overfitting. For this reason we assess the performance of the two estimators out of sample. Nevertheless, we also conducted an in-sample analysis that confirms that all the results that we present here referred to the out-of-sample performance also hold in sample.

[ Insert Table 3.9 Near Here ]

Table 3.9 reports the values of the entropy and the information potential of the forecasting errors achieved by the algorithm that minimizes the entropy and the one that minimizes the MSE. As in the previous simulation, there is a considerable difference between both the entropies ($-2.40$ versus $-1.99$) and the information potentials (7.33 versus 10.73), shedding light on the fact that the quadratic criterion is far from capturing the same level of information embedded in the time-series with respect to the information that the entropy does incorporate.

[ Insert Figures 3.4 and 3.5 Near Here ]

Figures 4 and 5 very well summarize the main conclusions that can be inferred from these simulations. They show how more much more accurate the entropic algorithm turns out to be with respect to the quadratic method. Figure 4 shows that the density of the forecasting error is much more concentrated around zero for the entropic algorithm, revealing a huge gap in the prediction accuracy. One may argue that the results could be affected by the specific choice of the number of past lags, therefore we repeat the experiment for several different numbers of lags.

While Figure 4 reports the results for $k = 3$ only, in order to convey the robustness of our findings Figure 5 plots the different density functions of the out-of-sample errors for four different values of $k$: 6, 12, 24 and 48. Very importantly, Figure 5 shows that the results are consistent across all the different choices of $k$. We also conducted other simulations with many different values of $k$ confirming our results. Since the figures plot the *out-of-sample* distribution of the forecasting errors, we can infer that the entropy effectively captures more of the information embedded in the time-series without overfitting the process in sample. This is absolutely key and makes the entropy a particularly relevant and appealing tool.

To further corroborate our results, Table 3.10 illustrates that all the first 20 central moments of the forecast distribution for the entropy are much closer to those of the observed time-series with respect to the prediction of the quadratic algorithm.

[ Insert Table 3.10 Near Here ]

Once again, the fact that this result has been achieved out of sample represents a very strong point of the entropy.

We however identify very few outliers because of which the high difference in the central moments of the errors between the two distributions would seem less apparent as it actually is. Therefore, we proceed as in the previous simulation: We first delete from the entropic distribution a few outliers from the tails and compare the moments of the new errors distribution with that of the MSE-based algorithm. Then, we compute the extended hit ratio to check whether these few outliers can be considered ”good” or ”bad” from the point of view of an investor.

[ Insert Table 3.11 and 3.12 Near Here ]

Tables 3.11 and 3.12 report, respectively, the first 4 moments of the forecasting errors distribution out of sample for the two algorithms and their first 20 central moments. As Figures 4 and 5 have clearly shown, the forecasting accuracy for the entropic algorithm is drastically higher than the quadratic one. The difference between the two algorithms grows at high pace when we progressively look at higher moments. The central moments of the forecasting errors for the entropy are of the order of magnitude $-17$ against $-9$ for the MSE for the 20th central moment. Significant differences can be found at any moment: regarding the kurtosis, for instance, the order of magnitude of the error for the entropy is $-5$ against $-4$ for the MSE.

[ Insert Tables 3.13 and 3.14 Near Here ]

Table 3.13 shows the hit ratio and the extended hit ratio for the two algorithms, always out of sample. The extended hit ratio is 27% for the entropy against 6% for the MSE, highlighting this overshooting effect of the entropic algorithm which does not appear to be relevant as far as the MSE-based method is concerned. The last step therefore consists of investigating how many of these overshoots can be beneficial or detrimental to an investor.

Table 3.14 deals with this issue and reports the results referred to 3 different cases. The first one gives an insight about these very few outliers that are produced by the entropic algorithm: 100% of the observations that lie below (above) the 1st (99th) percentile are "good" outliers for the investor in that they correctly predict the sign of the price change. This finding remains astonishing also when looking farther away from the deep tail: Considering the 5th and the 95 percentiles, still all the observations are positive outliers for the investor (300 out of 300), and considering the 10th and the 90th percentiles the number of good outliers for the investor becomes 584 out of 600, still a very high percentage (97.3%). Overall, the results are clearly in favor of the entropic algorithm, which ensures a hugely more precise forecast under model mis-specification and with the presence of non-linear and non-gaussian dynamics, and which can be effectively exploited by an investor.

[ Insert Table 3.15 Near Here ]

Indeed, Table 3.15 shows that the Sharpe ratio of an entropic strategy is much higher than the one achieved following the forecasting signals of the MSE, 8.25 for the entropy against 5.90 for the MSE. The same applies to the Sterling ratios. Table 3.15 reports the results with a very high multiplier, equal to 100 multiplied by the predicted increment, which leverages very much the strategy returns. With such an example we can show how beneficial it can be for an investor to rely on the prediction of the entropy instead of that of the MSE even for very aggressive strategies.

Our results corroborate the main two messages of the paper. First, as soon as the investor is unable to identify the correct model underlying the time-series of interest, the entropy can overcome this problem incorporating all the information embedded in the time-series into a linear projection that yields a much higher forecasting accuracy than a quadratic method. This is particularly relevant with respect to the interesting result put forward by Dacco et al. (1999) and Bradley et al. (2004), where it is shown that linear techniques can do at least as good as non-linear techniques out of sample. Our entropic methodology outperforms the quadratic criterion consistently across any value of $k$ and both in sample and out of sample. Second, as the DGP moves farther away from a two-moment setting, the differential between the forecasting accuracy of the entropic and the quadratic algorithm remarkably increases, confirming that the higher the degree of non-linearities and non-normality present in the data, the better it is to prefer an entropic criterion to a quadratic one.

## 3.5 Empirical analysis: the US GDP

In this section we investigate the performance of our estimators to forecast the series of the US GDP. We download the data from the FRED database of the Federal Reserve of Saint Louis. We analyze the series called "Percent change from preceding period, seasonally adjusted annual rate". This is the most common indicator to describe the evolution of the US economy. Data span Q1 1947 to Q4 2016 at quarterly frequency. We evaluate two different approaches. First, we put forward a novel entropic Markov switching estimation that builds on Hamilton (1989). Second, we assume model mis-specification and compare the performance of a linear projection based on the MSE as cost function and a linear projection based on the entropy. Given that the sample period comprises only 278 observations, an out-of-sample analysis would be meaningless and we therefore focus only on the in-sample forecasting. This is not an issue since we have already shown in the previous section that the entropic algorithm does not suffer from overfitting. Figure 6 shows the dynamics of this GDP growth rate for the whole sample period.

[ Insert Figure 3.6 Near Here ]

### 3.5.1 Correct model specification: a new entropic Markov-switching model

We start by proposing a novel entropic Markov switch in the flavor of Hamilton (1989). In his seminal paper, Hamilton (1989) shows how to compute the ”transition probabilities” in sample, which are defined as the probabilities to be in a certain state at a generic point in time $t+1$, conditional on the information available up to time $t$. For every $t$, the paper shows how to compute $Pr(S_{t+1} = 1 \mid \mathcal{F}_t)$ and $Pr(S_{t+1} = 2 \mid \mathcal{F}_t)$. Therefore, for each point in time $t$, we have at our disposal the probability that in $t+1$ we will be in state 1 and the probability that we will be in state 2. Needless to say, these two probabilities sum to 1. We make use of these probabilities to compute our forecast in sample as

$$\mathbb{E}\left[y_{t+1} \mid \mathcal{F}_t\right] = \mathbb{E}\left[y^{(1)}_{t+1} \mid \mathcal{F}_t\right] \, Pr(S_{t+1} = 1 \mid \mathcal{F}_t) + \mathbb{E}\left[y^{(2)}_{t+1} \mid \mathcal{F}_t\right] \, Pr(S_{t+1} = 2 \mid \mathcal{F}_t) \quad (3.50)$$

where $\mathbb{E}\left[y^{(k)}_{t+1} \mid \mathcal{F}_t\right]$ denotes the expected value of the process in case it will be in state $k$ at time $t+1$. These two expected values stem from the particular statistical model applied. Hamilton (1989) fits an AR(4) process for each state. In this paper we test for several different specifications to ensure the robustness of our findings. We follow Hamilton (1989), such that the process describing the GDP in state 1 writes

$$y^{(1)}_t = \alpha_0 + \alpha_1 \, y_{t-1} + \alpha_2 \, y_{t-2} + \alpha_3 \, y_{t-3} + \alpha_4 \, y_{t-4} + \epsilon_t \quad (3.51)$$

whereas in state 2 it writes

$$y_t^{(2)} = \beta_0 + \beta_1\, y_{t-1} + \beta_2\, y_{t-2} + \beta_3\, y_{t-3} + \beta_4\, y_{t-4} + v_t \tag{3.52}$$

such that we obtain that

$$\mathbb{E}\left[y_t^{(1)} \mid \mathcal{F}_t\right] = \alpha_0 + \alpha_1\, y_{t-1} + \alpha_2\, y_{t-2} + \alpha_3\, y_{t-3} + \alpha_4\, y_{t-4} \tag{3.53}$$

and

$$\mathbb{E}\left[y_t^{(2)} \mid \mathcal{F}_t\right] = \beta_0 + \beta_1\, y_{t-1} + \beta_2\, y_{t-2} + \beta_3\, y_{t-3} + \beta_4\, y_{t-4} \tag{3.54}$$

Since Hamilton (1989) estimates the set of 10 parameters $\hat{\alpha_0}$, $\hat{\alpha_1}$, $\hat{\alpha_2}$, $\hat{\alpha_3}$, $\hat{\alpha_4}$, $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$ and $\hat{\beta}_4$, we also assume to deal with two different linear projections, one per state, estimating the same set of the aforementioned 10 parameters. We keep the same filtered conditional probabilities estimated by Hamilton (1989), which we call $Pr(S_{t+1} = 1 \mid \mathcal{F}_t)$ and $Pr(S_{t+1} = 2 \mid \mathcal{F}_t)$. Our linear projection for the process at time $t+1$, conditional on the information set up to $t$, writes

$$\begin{aligned}\mathbb{E}\left[\hat{y}_{t+1} \mid \mathcal{F}_t\right] = Pr(S_{t+1} = 1 \mid \mathcal{F}_t)\ (\alpha_0 + \alpha_1\, y_{t-1} + \alpha_2\, y_{t-2} + \alpha_3\, y_{t-3} + \alpha_4\, y_{t-4}) + \\ + Pr(S_{t+1} = 2 \mid \mathcal{F}_t)\ (\beta_0 + \beta_1\, y_{t-1} + \beta_2\, y_{t-2} + \beta_3\, y_{t-3} + \beta_4\, y_{t-4})\end{aligned} \tag{3.55}$$

In our model, we do not need to estimate $Pr(S_{t+1} = 1 \mid \mathcal{F}_t)$ and $Pr(S_{t+1} = 2 \mid \mathcal{F}_t)$, since they are already provided by Hamilton (1989). In that respect, it is worth underscoring that in what follows we show that our method is able to outperform standard techniques despite the fact that it is essentially biased against: the probabilities have been derived in Hamilton (1989) jointly with a set of different model parameters through a maximum likelihood estimation. Nevertheless, our method shows a good performance even when using these probabilities that are not jointly estimated with the set of parameters of our own model. This sheds light on the merit of the entropic estimator.

In our model, we therefore need to estimate the 10 parameters above. At every time $t$ we compute the difference between the observed realized value $y_{t+1}$ and the model prediction $\hat{y}_{t+1}$. We end up having at our disposal a time-series of forecasting errors $e_t = y_t - \hat{y}_t$ for $t = 1, 2, ..., T$. Exactly as before, we still minimize the entropy of this unique error distribution, but with respect to 10 parameters ($\hat{\alpha_0}$, $\hat{\alpha_1}$, $\hat{\alpha_2}$, $\hat{\alpha_3}$, $\hat{\alpha_4}$, $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$ and $\hat{\beta}_4$), which enter, exactly as before, in our constraint of the estimator being linear and taking the form illustrated in equation (73).

For the sake of clearness and conciseness, we only present the density functions of the forecasting errors in sample.

[ Insert Figures 3.7, 3.8, 3.9 and 3.10 Near Here ]

Figure 7 shows the forecasting errors for the standard Markov switch implemented by Hamilton (1989), our entropic Markov switch and a single linear projection based on the MSE. Since in the previous section we have shown that incorporating more lags can be beneficial for the entropy, we use 20 lags for the the linear projection and for our entropic Markov switch. Results are striking: The entropy shrinks the errors distribution towards the origin more than the Markov switch by Hamilton (1989) and, even more, than the linear projection based on a quadratic criterion. This is striking because the entropy makes use of the transition probabilities estimated by a totally different model via maximum likelihood on a different set of parameters. Despite the fact that these probabilities have been estimated for a different model, the entropy can still outperform the other models.

Figure 8 shows that if we increase the number of past lags to 40, the difference between the entropy and the other models gets larger, since the entropy distribution is even taller and thinner than before with respect to the other tow distributions. This pattern is consistent with the findings that stem from our simulations illustrated in the previous section. The entropy can effectively take into account all the information in the time-series. Figures 9 and 10 confirm this pattern in two different specifications. Figure 9 shows that even if we extend the model by Hamilton (1989) increasing the number of lags to 40 exactly as for the entropy and the linear projection based on the MSE, nothing changes significantly: The entropy distribution still remains much more concentrated around 0. Moreover, Figure 10 represents these errors densities when we remove the constant from the autoregressive processes in the model by Hamilton (1989). In fact, the entropy and the linear projection do not encompass the presence of a constant, whereas the standard Markov switching model does. However, Figure 10 shows that also if we re-estimate the Markov switch without the constant, our results are not significantly affected.

### 3.5.2 Model mis-specification: linear projections

We finally move to describe the results of a simple linear entropic projection as tested in the previous section. We compare it with the standard Markov switch model and with a linear projection based on the MSE.

[ Insert Figures 3.11 and 3.12 Near Here ]

Figure 11 shows that a simple entropic linear projection of the last 4 observations in time can attain the same prediction accuracy as the standard Markov switch model, actually even slightly better than both the standard model and the linear projection based on the MSE.

[ Insert Figures 3.13 and 3.14 Near Here ]

To further corroborate our findings, Table 3.13 shows that the result is robust to whether the variance is allowed to change from a state to another or not. In all previous cases, the variance was assumed not to vary from state 1 to state 2 and *vice versa*. In Figure 13 we plot the errors distributions when the variance is allowed to vary in the standard Markov switch model from a state to another. As it can be clearly seen, results do not change significantly and are therefore very robust to the particular model specification.

To conclude, Figure 14 again points out of the most important findings of this paper. It plots the forecasting errors distributions when the number of past lags for the entropic and MSE-based linear projections increases up to 40. Incorporating more lags, once again the relative performance of the entropic estimator improves with respect to both the standard Markov switching model and the linear projection based on the quadratic criterion, since the distance between the errors distributions widens. Hence, we can infer once more that the entropy can be very beneficial in that it effectively captures all the information embedded in the time-series.

## 3.6 Conclusion

Two issues are crucial when forecasting the future values a time-series. First, it is well known that most economics and financial time-series exhibit non-linear and non-gaussian behavior. Accordingly, standard forecasting techniques based on quadratic cost functions turn out to be suboptimal, in that they cannot take into account the impact of the higher moments of the observed time-series. Second, observing the stochastic process generating the data is impossible, and detecting its precise form is most often too complex and unfeasible. This often leads to problems of model mis-specification, where the model postulated to describe the data is partially or totally unable to correctly describe the dynamics of the underlying process.

In the literature there have been many attempts to model and forecast economics and financial time-series. However, most of these approaches rely on economic assumptions, the validity of which can be questionable or which may not necessarily hold in every time period. Most of these assumptions are based on economic intuition, to try to overcome the impossibility to know the form of the data-generating process. The GDP is an enlightening example, in that it has been extensively modelled by postulating the existence of Markov-switches between different states. Starting from the seminal work of Hamilton (1989), which modelled the GDP as switching between the states of recession and expansion, many papers have proposed different models based on various economic intuitions, as, for example, the existence of a third state of moderate economic growth or time-varying switching probabilities from a state to another.

These economic assumptions are not the only limitation of such models. There are also some statistical assumptions that can be restrictive or that may invalidate the accuracy of the results and their predictive ability out of sample. For instance, it is not clear in the literature whether a linear or a non-linear model would yield the highest forecasting accuracy out of sample when dealing with non-linearities in the data that cannot be identified precisely. Moreover, in the set of all the non-linear techniques proposed in the literature, it is still a puzzling issue which ones would be more suitable to forecast out of sample when the form of the stochastic process is not known.

To deal with all these issues, in this paper we have proposed a new forecasting algorithm based on the minimization of the entropy of the forecasting error. We have discussed how much the entropy has been applied in economics and finance but surprisingly not in forecasting, despite its appealing properties, unfolding a crucial gap that we have filled. In particular, we have shown how beneficial the adoption of an entropic cost function can be. From a statistical point of view, we have shown that the entropy is able to extrapolate all the information embedded in the time-series without overfitting the process, since it captures the impact of the higher moments and the dynamics of the underlying stochastic process by estimating the whole density function of the data. On the other hand, any quadratic criterion takes into account the information conveyed by the first two moments only.

We have developed a non-parametric entropic forecasting algorithm that *i)* does not rely on any economic assumption, *ii)* does not require the specification of a particular model to describe the data, *iii)* can be effectively applied to any time-series in any time period, and *iv)* identifies and exploits all the information incorporated in the observed data without suffering from overfitting when forecasting out of sample. We have established a stochastic dominance criterion between such an entropic algorithm and a standard forecasting algorithm that employs the MSE as cost function. In a Gaussian and linear environment, assuming correct model specification, the entropy yields the same predictive accuracy as the MSE. However, when *i)* the stochastic process generating the data is non-linear, *ii)* the noise is non-Gaussian, and *iii)* there is model mis-specification due to the impossibility to observe the process underlying the data, the entropic algorithm strongly outperforms the MSE-based one on a variety of target functionals, both in sample and out of sample.

We have applied our entropic algorithm on the series of the US GDP, proposing two different approaches. First, in the case of correct model specification, we have put forward a novel entropic Markov switch building on the work by Hamilton (1989). This new model uses the filtered probabilities to switch from a state to another from Hamilton (1989) but estimating the weights attached to the past observations through an entropic criterion. Second, in case of model mis-specification, we have employed a linear projection to forecast the future values of the GDP growth rates. We have compared a linear projection where the weights are calibrated by means of an entropic criterion, a linear projection based on the MSE as cost function, and the standard Markov-switching model of Hamilton (1989). We have shown that the entropy can be highly beneficial in that it can shrink more towards zero the distribution of the forecasting errors in all cases analyzed. In addition, its predictive accuracy remarkable increases when incorporating more past lags in the forecast, unlike the MSE-based projection which does not benefit as much as the entropy, given that the latter uses all the information in the data and not only the one embedded in the first two moments.

One of the strongest points of this research does not lie only in the higher predictive accuracy of the entropy in a simulated scenario, nor in the new entropic Markov switch that we put forward and that we apply to forecast the GDP. A key and influential element stemming from our results is the vast applicability of such entropic techniques to many time-series in economics and finance. Our fully non-parametric methods ensure high predictive accuracy without the need to specify economic assumptions or to try to identify the form of the underlying stochastic process, being able to consistently yield excellent results under both correct model specification and moded mis-specification. Hence, they can be effectively applied in any other application in finance and economics where the data may be generated by a non-linear and non-gaussian process almost impossible to be precisely identified.

## 3.7 Appendix

Figure 3.1: On the left, the dynamics of the variance for the class of densities described by equations (3.4) and (3.5) as a function of the free parameter $\alpha$. On the right, the dynamics of the entropy for the same distributions as a function of *alpha*. The minimum of the variance is attained for $\alpha = 1$, in correspondence of which the entropy is almost at its global maximum. The two criteria lead therefore to opposite choices.

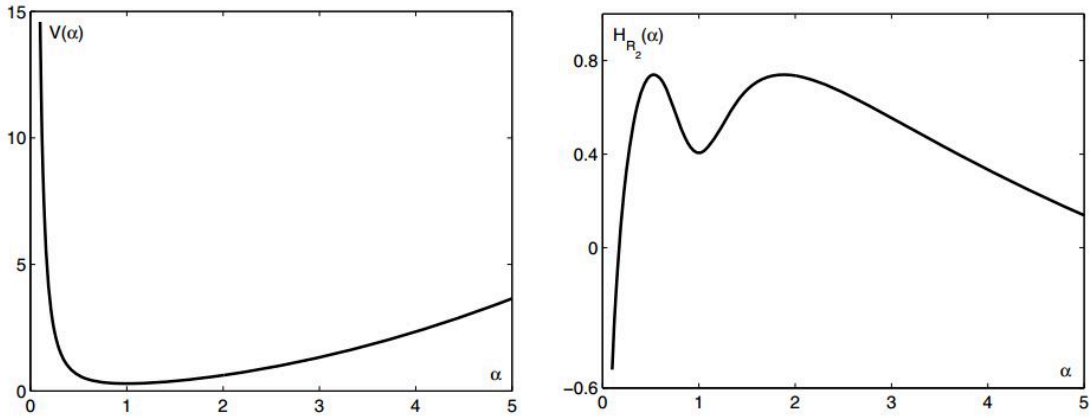



Figure 3.2: Empirical density functions of the forecasting errors out of sample for the entropic and the MSE-based algorithms. The weights for the linear projection are computed over a sample of 6,000 observations. The out-of-sample test is performed on a period comprising 3,000 observations. The underlying stochastic process generating the time-series is an AR(3) with fixed parameters and gaussian innovations. We assume to be under correct model specification, each of the two forecasting algorithms linearly projects the last 3 observations in time.

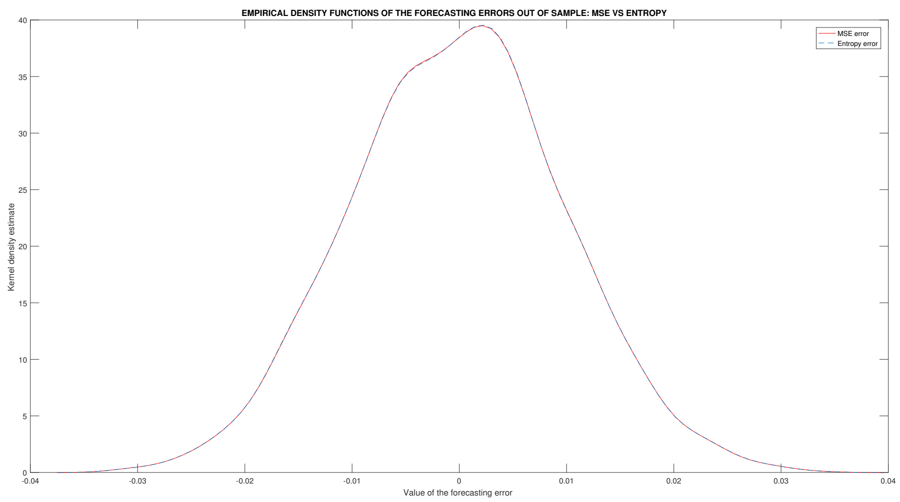


Figure 3.3

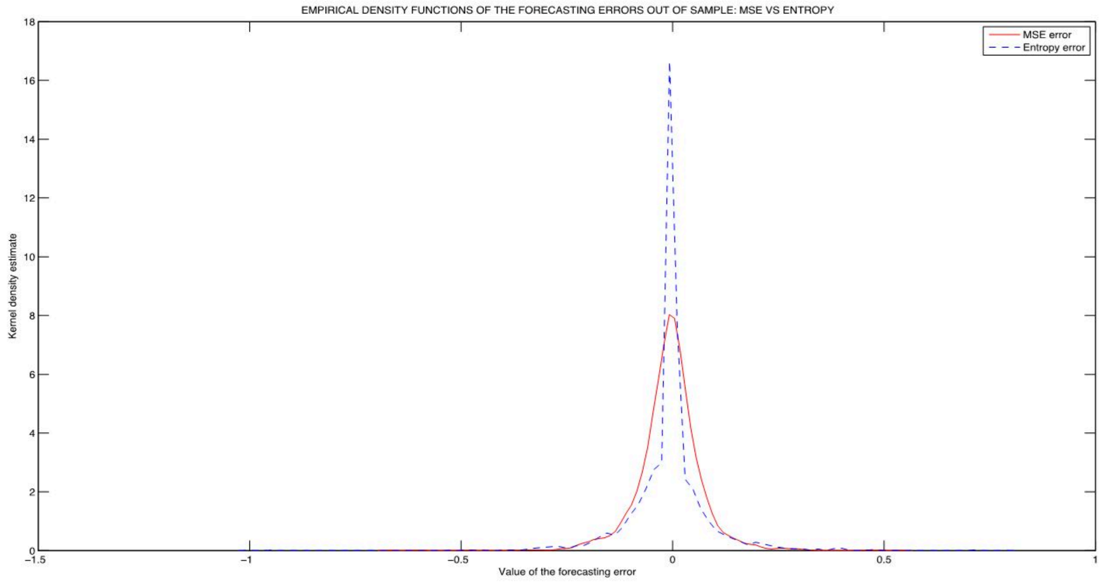



Figure 3.4: Out-of-sample distributions of the forecasting errors for the entropic and the quadratic algorithms. The forecast is a linear projection of the past 3 pags. The computation of the weights associated to each past observation is made on a sample of 6,000 observations, whereas the out of sample comprises 3,000 data points. The stochastic process generating the data is a non-linear process with CMGY noise and a two-state Markov switch. We assume to be under model mis-specification, since the investor makes use of a linear projection to approximate the dynamics of a non-linear process.

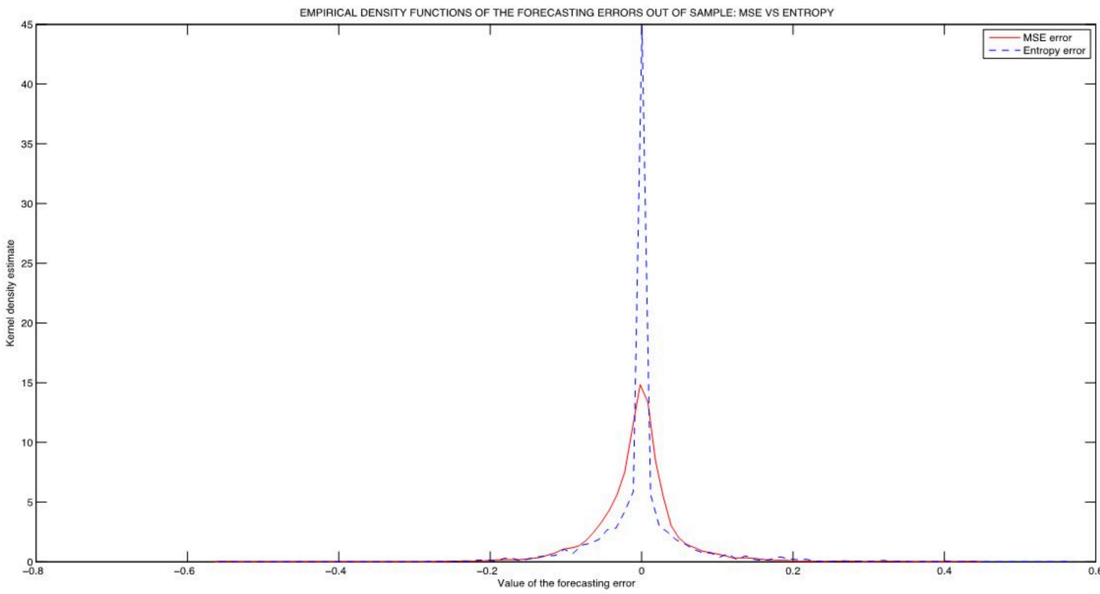
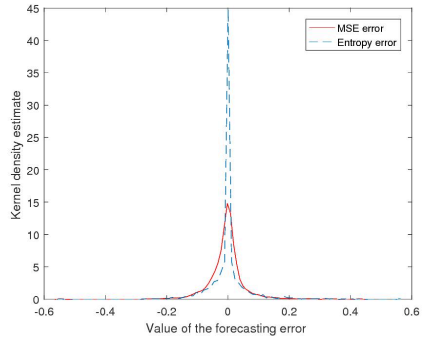
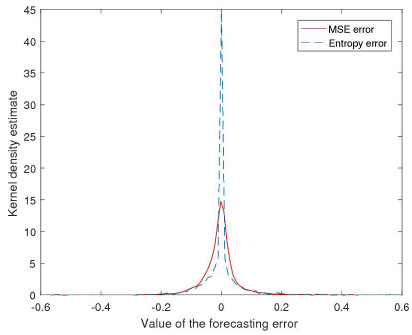


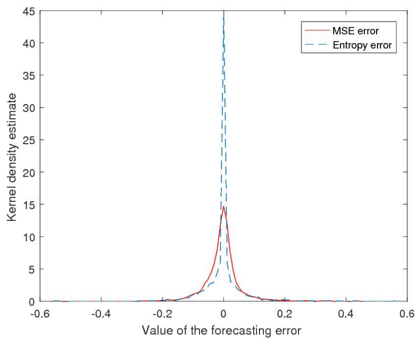
Figure 3.5: This figure shows the density functions of the forecasting errors out of sample for the entropic and the quadratic estimators. Each sub-figure plots the results for a different number of past observations $k$ included in the linear projection. Data are simulated from a Markov switching process with non-linear dynamics in each of the two states, as described in Section 3.3.



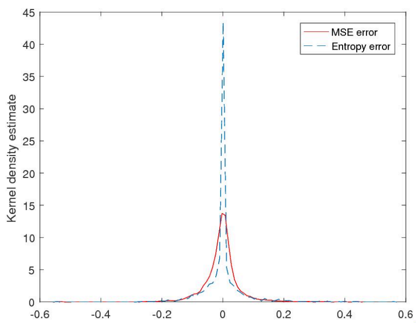

(a) Number of past lags: $k = 6$




(b) Number of past lags: $k = 12$




(c) Number of past lags: $k = 24$




(d) Number of past lags: $k = 48$

Figure 3.6: Quarterly data referred to the GDP growth rate from Q1 1947 to Q4 2016. *Source: FRED Saint Louis.*

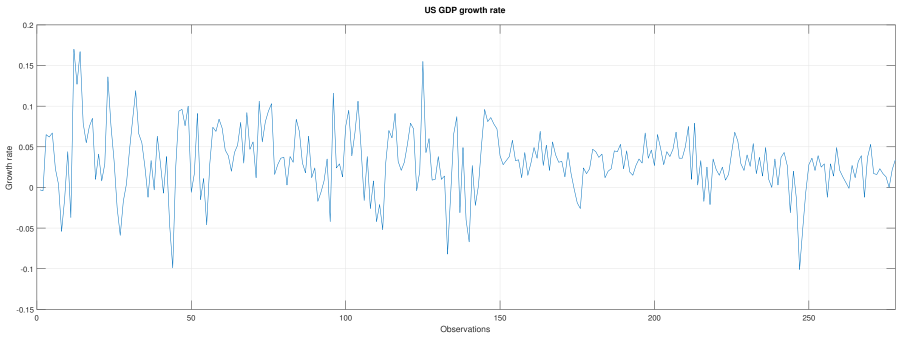



Figure 3.7: Empirical density functions of the forecasting errors for 3 different models. The green line refers to the standard Markov-switching model put forward by Hamilton (1989). The blue line represents our entropic Markov switch that uses the filtered probabilities estimated as in Hamilton (1989), where for each state the forecast is a linear projection of the past 20 observations in time. The red line describes the results of a single linear projection of the last 20 observations with the MSE as cost function.

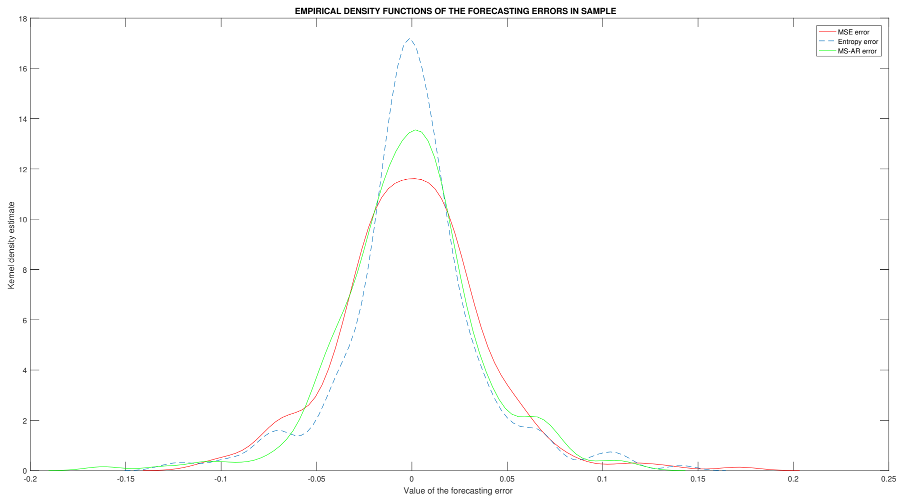


Figure 3.8: Empirical density functions of the forecasting errors for 3 different models. The green line refers to the standard Markov-switching model put forward by Hamilton (1989). The blue line represents our entropic Markov switch that uses the filtered probabilities estimated as in Hamilton (1989), where for each state the forecast is a linear projection of the past 40 observations in time. The red line describes the results of a single linear projection of the last 40 observations with the MSE as cost function.

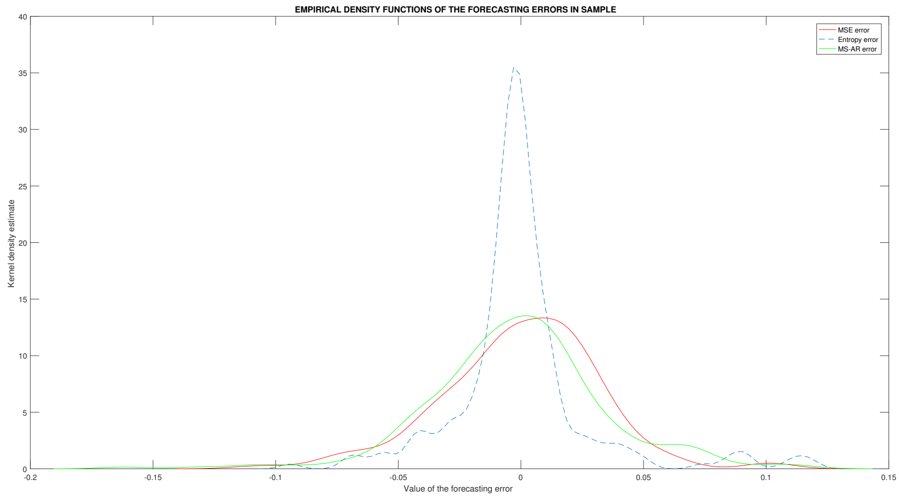



Figure 3.9: Empirical density functions of the forecasting errors for 3 different models. The green line refers to the standard Markov-switching model put forward by Hamilton (1989), where however in each of the two states the model is not an AR(4) anymore but it is extended to an AR(40). The blue line represents our entropic Markov switch that uses the filtered probabilities estimated as in Hamilton (1989), where for each state the forecast is a linear projection of the past 40 observations in time. The red line describes the results of a single linear projection of the last 40 observations with the MSE as cost function.

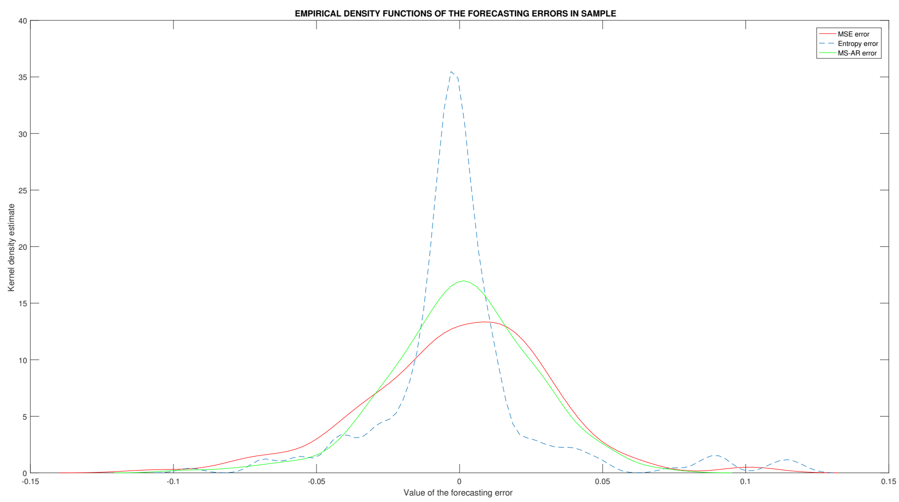


Figure 3.10: Empirical density functions of the forecasting errors for 3 different models. The green line refers to the standard Markov-switching model put forward by Hamilton (1989), where however in each of the two states the model is not an AR(4) anymore but it is extended to an AR(40). In addition, we remove the constant from the autoregressive model for the sake of comparability with the entropy (see Section 3.5 for more details). The blue line represents our entropic Markov switch that uses the filtered probabilities estimated as in Hamilton (1989), where for each state the forecast is a linear projection of the past 40 observations in time. The red line describes the results of a single linear projection of the last 40 observations with the MSE as cost function.

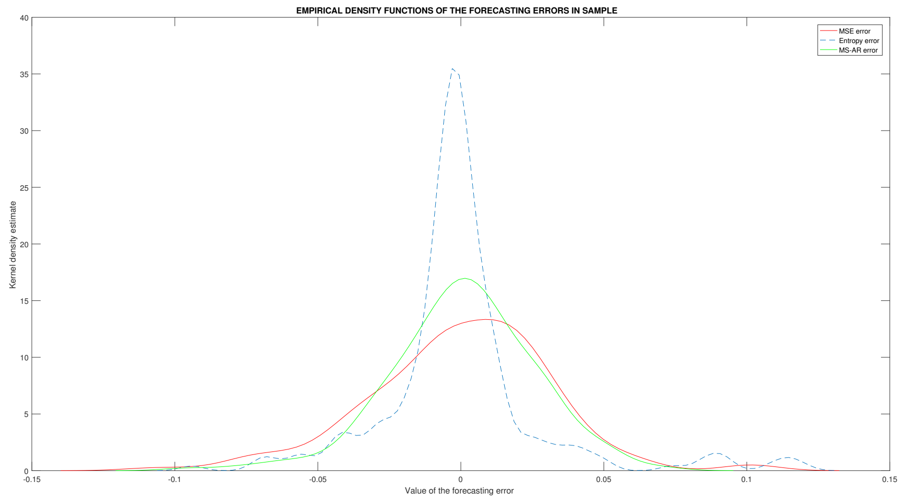


Figure 3.11: Empirical density functions of the forecasting errors for 3 different models. The green line refers to the standard Markov-switching model put forward by Hamilton (1989). The blue line represents our entropic linear projection of the last 4 observations in time, consistent with the choice of Hamilton (1989) to fit an AR(4) process to each of the two states. In the same fashion, the red line describes the results of a single linear projection of the last 4 observations with the MSE as cost function.

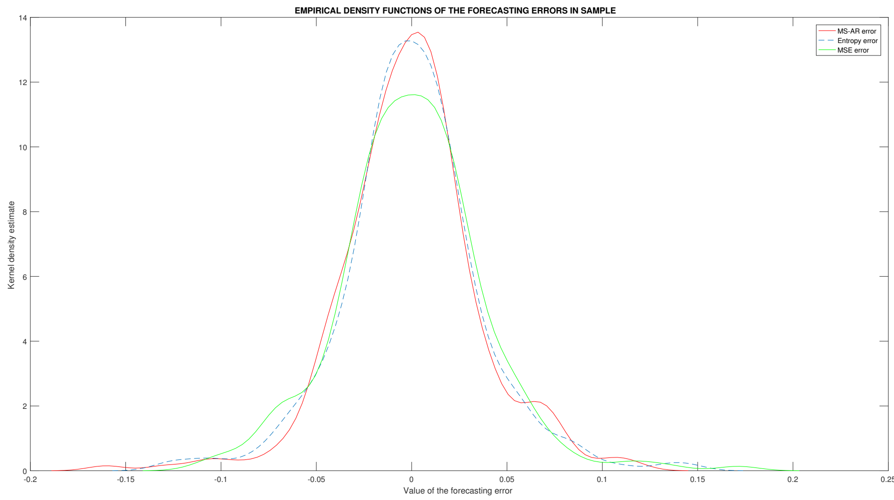



Figure 3.12: Empirical density functions of the forecasting errors for 3 different models. The green line refers to the standard Markov-switching model put forward by Hamilton (1989). The blue line represents our entropic linear projection of the last 20 observations in time. In the same fashion, the red line describes the results of a single linear projection of the last 20 observations with the MSE as cost function.

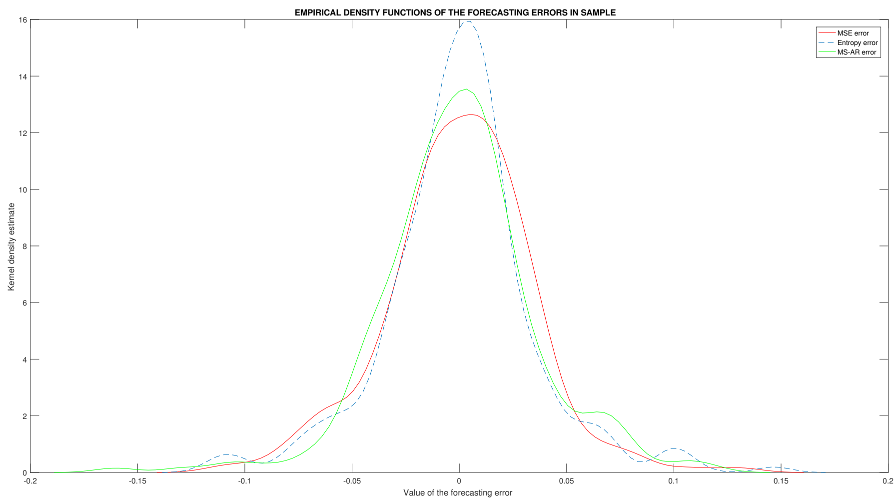


Figure 3.13: Empirical density functions of the forecasting errors for 3 different models. The green line refers to the standard Markov-switching model put forward by Hamilton (1989). The blue line represents our entropic linear projection of the last 20 observations in time. In the same fashion, the red line describes the results of a single linear projection of the last 20 observations with the MSE as cost function. The difference with the baseline model by Hamilton (1989) is that we do not let the variance change across states in his model specification, but it is constant across states.

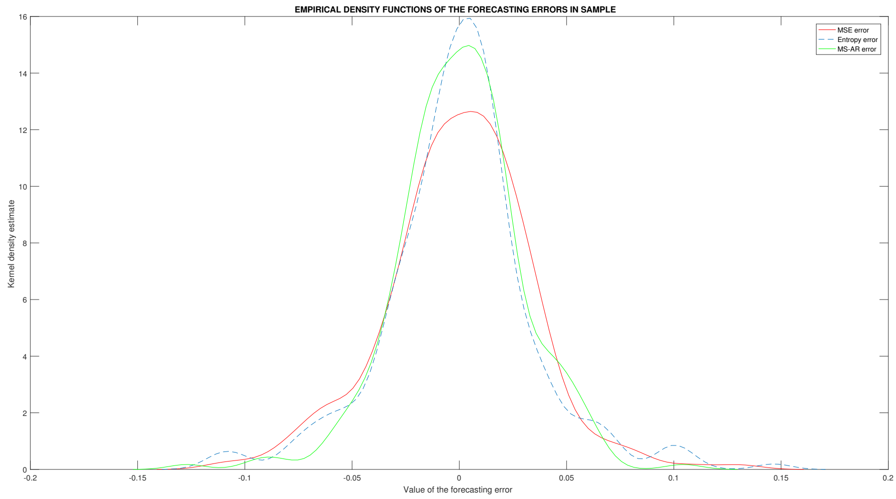



Figure 3.14: Empirical density functions of the forecasting errors for 3 different models. The green line refers to the standard Markov-switching model put forward by Hamilton (1989). The blue line represents our entropic linear projection of the last 40 observations in time. In the same fashion, the red line describes the results of a single linear projection of the last 40 observations with the MSE as cost function. The difference with the baseline model by Hamilton (1989) is that we do not let the variance change across states in his model specification, but it is constant across states.

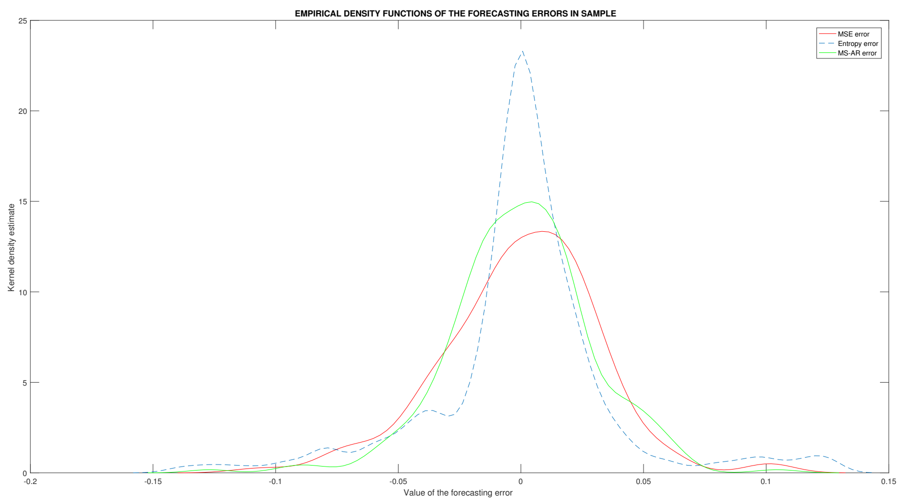


Table 3.1: The table reports the first 4 moments of the forecasting error distributions out of sample for the entropic and the quadratic algorithms. The data generating process is an AR(3) with gaussian innovations. We assume to be under the case of correct model specification. The computation of the weights of the linear projection of the past 3 observations in sample is made on a set of 6,000 points, whereas the out-of-sample test is run on a set of 3,000 points.

| | MSE algorithm | Entropic algorithm |
|---|---:|---:|
| Mean | 0 | 0 |
| StD | 0.010 | 0.010 |
| Skewness | 0.019 | 0.018 |
| Kurtosis | 2.923 | 2.921 |

Table 3.2: The table reports the first 4 moments of the forecasting error distributions out of sample for the entropic and the quadratic algorithms. The data generating process is an AR(3) with gaussian innovations. We assume to be under the case of correct model specification. The computation of the weights of the linear projection of the past 3 observations in sample is made on a set of 6,000 points, whereas the out-of-sample test is run on a set of 3,000 points.

| $k$ | $\mathbb{E}\left[(e^{MSE} - \mu_e^{MSE})^k\right]$ | $\mathbb{E}\left[(e^{Ent} - \mu_e^{Ent})^k\right]$ |
|---|---:|---:|
| 1 | 0 | 0 |
| 2 | $9.765 \cdot 10^{-5}$ | $9.770 \cdot 10^{-5}$ |
| 3 | $1.806 \cdot 10^{-8}$ | $1.706 \cdot 10^{-8}$ |
| 4 | $2.787 \cdot 10^{-8}$ | $2.788 \cdot 10^{-8}$ |
| 5 | $2.607 \cdot 10^{-11}$ | $2.525 \cdot 10^{-11}$ |
| 6 | $1.265 \cdot 10^{-11}$ | $1.265 \cdot 10^{-11}$ |
| 7 | $2.569 \cdot 10^{-14}$ | $2.475 \cdot 10^{-14}$ |
| 8 | $7.504 \cdot 10^{-15}$ | $7.491 \cdot 10^{-15}$ |
| 9 | $2.450 \cdot 10^{-17}$ | $2.343 \cdot 10^{-17}$ |
| 10 | $5.256 \cdot 10^{-18}$ | $5.241 \cdot 10^{-18}$ |
| 11 | $2.402 \cdot 10^{-20}$ | $2.287 \cdot 10^{-20}$ |
| 12 | $4.103 \cdot 10^{-21}$ | $4.088 \cdot 10^{-21}$ |
| 13 | $2.441 \cdot 10^{-23}$ | $2.324 \cdot 10^{-23}$ |
| 14 | $3.449 \cdot 10^{-24}$ | $3.437 \cdot 10^{-24}$ |
| 15 | $2.561 \cdot 10^{-26}$ | $2.445 \cdot 10^{-26}$ |
| 16 | $3.058 \cdot 10^{-27}$ | $3.049 \cdot 10^{-27}$ |
| 17 | $2.750 \cdot 10^{-29}$ | $2.641 \cdot 10^{-29}$ |
| 18 | $2.821 \cdot 10^{-30}$ | $2.816 \cdot 10^{-30}$ |
| 19 | $3.005 \cdot 10^{-32}$ | $2.905 \cdot 10^{-32}$ |
| 20 | $2.685 \cdot 10^{-32}$ | $2.684 \cdot 10^{-33}$ |

Table 3.3: Values of the entropy and information potential of the forecasting error attained by the minima of the quadratic and the entropic algorithms respectively (at the end of the training for the entropic algorithm). This in-sample analysis is made on 6,000 observations. The high difference in the information potential of the error reveals that the quadratic technique is far from taking into account all the information in the series of errors.

| | MSE | Entropy |
|---|---|---|
| Entropy in sample | -1,456 | -2,029 |
| Information potential | 4,288 | 7,605 |

Table 3.4: First 20 central moments of the observed out-of-sample distribution of the time-series of interest, the forecast made by the quadratic criterion and that of the entropic algorithm. The forecast produced by the entropic method clearly matches much better the moments with those of the true time-series to be forecasted.

| $k$ | $\mathbb{E}\left[(x-\mu_x)^k\right]$ | $\mathbb{E}\left[\left(\hat{x}^{MSE}-\mu_{\hat{x}}^{MSE}\right)^k\right]$ | $\mathbb{E}\left[\left(\hat{x}^{Ent}-\mu_{\hat{x}}^{Ent}\right)^k\right]$ |
|---|---:|---:|---:|
| 1 | 0 | 0 | 0 |
| 2 | $6.476 \cdot 10^{-3}$ | $8.852 \cdot 10^{-4}$ | $5.591 \cdot 10^{-3}$ |
| 3 | $-1.789 \cdot 10^{-4}$ | $-5.771 \cdot 10^{-6}$ | $-3.227 \cdot 10^{-8}$ |
| 4 | $3.228 \cdot 10^{-4}$ | $6.944 \cdot 10^{-6}$ | $3.067 \cdot 10^{-4}$ |
| 5 | $-4.304 \cdot 10^{-5}$ | $-1.882 \cdot 10^{-7}$ | $1.811 \cdot 10^{-6}$ |
| 6 | $4.968 \cdot 10^{-5}$ | $1.741 \cdot 10^{-7}$ | $5.536 \cdot 10^{-5}$ |
| 7 | $-1.278 \cdot 10^{-5}$ | $-8.134 \cdot 10^{-9}$ | $-1.098 \cdot 10^{-6}$ |
| 8 | $1.170 \cdot 10^{-5}$ | $6.306 \cdot 10^{-9}$ | $1.417 \cdot 10^{-5}$ |
| 9 | $-4.043 \cdot 10^{-6}$ | $-3.820 \cdot 10^{-10}$ | $-1.004 \cdot 10^{-6}$ |
| 10 | $3.237 \cdot 10^{-6}$ | $2.566 \cdot 10^{-10}$ | $4.067 \cdot 10^{-6}$ |
| 11 | $-1.323 \cdot 10^{-6}$ | $-1.881 \cdot 10^{-11}$ | $-5.445 \cdot 10^{-7}$ |
| 12 | $9,742 \cdot 10^{-7}$ | $1.102 \cdot 10^{-11}$ | $1.239 \cdot 10^{-6}$ |
| 13 | $-4.446 \cdot 10^{-7}$ | $-9.537 \cdot 10^{-13}$ | $-2.495 \cdot 10^{-7}$ |
| 14 | $3.092 \cdot 10^{-7}$ | $4.888 \cdot 10^{-13}$ | $3.931 \cdot 10^{-7}$ |
| 15 | $-1.524 \cdot 10^{-7}$ | $-4.911 \cdot 10^{-14}$ | $-1.051 \cdot 10^{-7}$ |
| 16 | $1.018 \cdot 10^{-7}$ | $2.222 \cdot 10^{-14}$ | $1.285 \cdot 10^{-7}$ |
| 17 | $-5.297 \cdot 10^{-8}$ | $-2.546 \cdot 10^{-15}$ | $-4.218 \cdot 10^{-8}$ |
| 18 | $3.432 \cdot 10^{-8}$ | $1.030 \cdot 10^{-15}$ | $4.296 \cdot 10^{-8}$ |
| 19 | $-1.859 \cdot 10^{-8}$ | $-1.322 \cdot 10^{-16}$ | $-1.640 \cdot 10^{-8}$ |
| 20 | $1.178 \cdot 10^{-8}$ | $4.845 \cdot 10^{-17}$ | $1.462 \cdot 10^{-8}$ |

Table 3.5: The first 4 moments of the distribution of the forecasting errors for the quadratic algorithm and the entropic one.

| | MSE algorithm | Entropic algorithm |
|---|---|---|
| Mean | $-6.549 \cdot 10^{-3}$ | $-5.263 \cdot 10^{-3}$ |
| StD | $7.583 \cdot 10^{-2}$ | $6.692 \cdot 10^{-2}$ |
| Skewness | $-0.392$ | $-0.091$ |
| Kurtosis | 11.568 | 6.553 |

Table 3.6: First 20 central moments of the forecasting errors distribution for both the quadratic and the entropic algorithm out of sample.

| $k$ | $\mathbb{E}\left[(e^{MSE} - \mu_e^{MSE})^k\right]$ | $\mathbb{E}\left[(e^{Ent} - \mu_e^{Ent})^k\right]$ |
|---|---|---|
| 1 | 0 | 0 |
| 2 | $5.748 \cdot 10^{-3}$ | $4.477 \cdot 10^{-3}$ |
| 3 | $-1.711 \cdot 10^{-4}$ | $-2.724 \cdot 10^{-5}$ |
| 4 | $3.823 \cdot 10^{-4}$ | $1.313 \cdot 10^{-4}$ |
| 5 | $-6.994 \cdot 10^{-5}$ | $-2.129 \cdot 10^{-7}$ |
| 6 | $8.807 \cdot 10^{-5}$ | $5.822 \cdot 10^{-6}$ |
| 7 | $-3.022 \cdot 10^{-5}$ | $6.032 \cdot 10^{-10}$ |
| 8 | $2.905 \cdot 10^{-5}$ | $3.063 \cdot 10^{-7}$ |
| 9 | $-1.275 \cdot 10^{-5}$ | $-5.949 \cdot 10^{-10}$ |
| 10 | $1.061 \cdot 10^{-5}$ | $1.767 \cdot 10^{-8}$ |
| 11 | $-5.306 \cdot 10^{-6}$ | $-1.120 \cdot 10^{-10}$ |
| 12 | $4.045 \cdot 10^{-6}$ | $1.078 \cdot 10^{-9}$ |
| 13 | $-2.197 \cdot 10^{-6}$ | $-1.279 \cdot 10^{-11}$ |
| 14 | $1.583 \cdot 10^{-6}$ | $6.834 \cdot 10^{-11}$ |
| 15 | $-9.081 \cdot 10^{-7}$ | $-1.215 \cdot 10^{-12}$ |
| 16 | $6.307 \cdot 10^{-7}$ | $4.449 \cdot 10^{-12}$ |
| 17 | $-3.756 \cdot 10^{-7}$ | $-1.056 \cdot 10^{-13}$ |
| 18 | $2.547 \cdot 10^{-7}$ | $2.954 \cdot 10^{-13}$ |
| 19 | $-1.557 \cdot 10^{-7}$ | $-8.731 \cdot 10^{-15}$ |
| 20 | $1.040 \cdot 10^{-7}$ | $1.991 \cdot 10^{-14}$ |

Table 3.7: The table summarizes the fraction of total ”good” outliers with respect to the ”bad” ones for the entropic algorithm. The first column shows the percentile for the left (right) tail; all the observations falling below (above) this threshold are counted. We look at how many of these observations do predict the correct direction of the price change. As the table displays, almost all outliers are classified as ”good” for the investor, in that they do identify correctly the future direction of the price change.

| Error percentiles | Left Tail | Right Tail |
|---|---|---|
| 1-99 | 30/30 | 30/30 |
| 5-95 | 149/150 | 149/150 |
| 10-90 | 297/300 | 291/300 |

Table 3.8: ”Hit ratio” and ”Extended hit ratio” for both algorithms. Our hit ratio is computed by looking at how many times the estimator correctly predicts, at time $t$, the market direction in $t+1$, *i.e.* the sign of the price change. The extended hit ratio identifies the ”good” outliers for the investor: it represents the fraction of observations where the estimator correctly predicted the sign of the price change, and it estimated a larger price change than the one that actually occurred.

| | MSE | Entropy |
|---|---|---|
| Hit ratio (in %) | 65,27% | 66,13% |
| Extended hit ratio (in %) | 6,33% | 28,83% |

Table 3.9: Value of the in-sample entropy and information potential for the algorithm that minimizes the entropy and the one that minimizes the mean square error.

| | MSE algorithm | Entropic algorithm |
|---|---|---|
| Entropy in sample | $-1.992$ | $-2.396$ |
| Information potential | 7.328 | 10.73 |

Table 3.10: Value of the first 20 central moments of the observed time-series, and of the series predicted by the algorithms that minimize, respectively, the mean square error and the entropy.

| $k$ | $\mathbb{E}\left[(x-\mu_x)^k\right]$ | $\mathbb{E}\left[\left(\hat{x}^{MSE}-\mu_{\hat{x}}^{MSE}\right)^k\right]$ | $\mathbb{E}\left[\left(\hat{x}^{Ent}-\mu_{\hat{x}}^{Ent}\right)^k\right]$ |
|---|---|---|---|
| 1 | 0 0 | 0 0 | 0 |
| 2 | $6.81 \cdot 10^{-3}$ | $1.69 \cdot 10^{-4}$ | $9.55 \cdot 10^{-3}$ |
| 3 | $3.23 \cdot 10^{-4}$ | $3.85 \cdot 10^{-5}$ | $7.53 \cdot 10^{-5}$ |
| 4 | $9.95 \cdot 10^{-5}$ | $8.63 \cdot 10^{-6}$ | $8.66 \cdot 10^{-5}$ |
| 5 | $5.33 \cdot 10^{-5}$ | $0.15 \cdot 10^{-7}$ | $8.85 \cdot 10^{-6}$ |
| 6 | $4.39 \cdot 10^{-6}$ | $1.20 \cdot 10^{-8}$ | $8.28 \cdot 10^{-7}$ |
| 7 | $7.26 \cdot 10^{-6}$ | $9.36 \cdot 10^{-10}$ | $9.83 \cdot 10^{-8}$ |
| 8 | $0.84 \cdot 10^{-6}$ | $5.59 \cdot 10^{-11}$ | $2.33 \cdot 10^{-8}$ |
| 9 | $0.25 \cdot 10^{-6}$ | $0.25 \cdot 10^{-12}$ | $3.79 \cdot 10^{-9}$ |
| 10 | $5.02 \cdot 10^{-7}$ | $6.54 \cdot 10^{-13}$ | $1.35 \cdot 10^{-10}$ |
| 11 | $8.43 \cdot 10^{-7}$ | $8.17 \cdot 10^{-14}$ | $1.02 \cdot 10^{-10}$ |
| 12 | $5.06 \cdot 10^{-7}$ | $0.55 \cdot 10^{-14}$ | $4.86 \cdot 10^{-11}$ |
| 13 | $8.79 \cdot 10^{-8}$ | $1.11 \cdot 10^{-15}$ | $6.57 \cdot 10^{-12}$ |
| 14 | $1.55 \cdot 10^{-8}$ | $2.01 \cdot 10^{-16}$ | $3.19 \cdot 10^{-12}$ |
| 15 | $1.82 \cdot 10^{-8}$ | $2.87 \cdot 10^{-17}$ | $1.07 \cdot 10^{-13}$ |
| 16 | $1.49 \cdot 10^{-8}$ | $3.99 \cdot 10^{-18}$ | $4.13 \cdot 10^{-14}$ |
| 17 | $0.42 \cdot 10^{-9}$ | $5.16 \cdot 10^{-19}$ | $7.82 \cdot 10^{-14}$ |
| 18 | $1.80 \cdot 10^{-9}$ | $6.55 \cdot 10^{-20}$ | $3.13 \cdot 10^{-15}$ |
| 19 | $6.73 \cdot 10^{-9}$ | $8.07 \cdot 10^{-21}$ | $0.49 \cdot 10^{-15}$ |
| 20 | $8.01 \cdot 10^{-10}$ | $9.82 \cdot 10^{-22}$ | $5.63 \cdot 10^{-16}$ |

Table 3.11: First 4 moments of the error distribution generated by the algorithms that minimize, respectively, the mean square error and the entropy.

| | MSE algorithm | Entropic algorithm |
|---|---|---|
| Mean | $-5.141 \cdot 10^{-3}$ | $-1.751 \cdot 10^{-3}$ |
| Standard Dev | $5.531 \cdot 10^{-2}$ | $4.562 \cdot 10^{-2}$ |
| Skewness | 0.233 | 0.345 |
| Kurtosis | 12.273 | 7.051 |

Table 3.12: First 20 central moments of the error distribution generated by the algorithms that minimize, respectively, the mean square error and the entropy.

| $k$ | $\mathbb{E}\left[(e^{MSE} - \mu_e^{MSE})^k\right]$ | $\mathbb{E}\left[(e^{Ent} - \mu_e^{Ent})^k\right]$ |
|---|---|---|
| 1 | 0 | 0 |
| 2 | $3.059 \cdot 10^{-3}$ | $2.081 \cdot 10^{-3}$ |
| 3 | $3.948 \cdot 10^{-5}$ | $3.276 \cdot 10^{-5}$ |
| 4 | $1.148 \cdot 10^{-4}$ | $3.053 \cdot 10^{-5}$ |
| 5 | $-2.134 \cdot 10^{-6}$ | $1.500 \cdot 10^{-6}$ |
| 6 | $1.476 \cdot 10^{-5}$ | $6.944 \cdot 10^{-7}$ |
| 7 | $-2.619 \cdot 10^{-6}$ | $5.659 \cdot 10^{-8}$ |
| 8 | $3.160 \cdot 10^{-6}$ | $1.922 \cdot 10^{-8}$ |
| 9 | $-1.018 \cdot 10^{-6}$ | $2.074 \cdot 10^{-9}$ |
| 10 | $8.076 \cdot 10^{-7}$ | $5.905 \cdot 10^{-10}$ |
| 11 | $-3.314 \cdot 10^{-7}$ | $7.580 \cdot 10^{-11}$ |
| 12 | $2.206 \cdot 10^{-7}$ | $1.933 \cdot 10^{-11}$ |
| 13 | $-1.017 \cdot 10^{-7}$ | $2.783 \cdot 10^{-12}$ |
| 14 | $6.205 \cdot 10^{-8}$ | $6.589 \cdot 10^{-13}$ |
| 15 | $-3.046 \cdot 10^{-8}$ | $1.028 \cdot 10^{-13}$ |
| 16 | $1.770 \cdot 10^{-8}$ | $2.312 \cdot 10^{-14}$ |
| 17 | $-9.008 \cdot 10^{-9}$ | $3.821 \cdot 10^{-15}$ |
| 18 | $5.091 \cdot 10^{-9}$ | $8.292 \cdot 10^{-16}$ |
| 19 | $-2.647 \cdot 10^{-9}$ | $1.430 \cdot 10^{-16}$ |
| 20 | $1.471 \cdot 10^{-9}$ | $3.023 \cdot 10^{-17}$ |

Table 3.13: Hit Ratio and Extended Hit Ratio of the error distribution generated by the algorithms that minimize, respectively, the mean square error and the entropy.

| | MSE algorithm | Entropic algorithm |
|---|---|---|
| Hit ratio (in %) | 68.60% | 69.60% |
| Extended hit ratio (in %) | 5.97% | 27.12% |

Table 3.14: The table summarizes the fraction of total "good" outliers with respect to the "bad" ones for the entropic algorithm. The first column shows the percentile for the left (right) tail; all the observations falling below (above) this threshold are counted. We look at how many of these observations do predict the correct direction of the price change.

| Error Percentiles | Left Tail | Right Tail |
|---|---|---|
| 1-99 | 30/30 | 30/30 |
| 5-95 | 150/150 | 150/150 |
| 10-90 | 298/300 | 286/300 |

Table 3.15: Sharpe ratio and Sterling ratio for two strategies based, respectively, on the forecasting signals of the entropy and the MSE. The

| | MSE | Entropy |
|---|---|---|
| Sharpe ratio | 5.902 | 8.246 |
| Sterling ratio | $2.238\,10^5$ | $1.871\,10^8$ |

# Chapter 4

# Can liquidity risk explain the pairs trading anomaly?[*]


## Abstract

We aim to shed light on the channel linking liquidity risk and pairs trading. We build on the work of Frino et al. (2003), who show that an ideal setting is provided by the Italian stock market, which enforced in 2001 a highly specific reform aiming at increasing liquidity by means of very *ad hoc* rules. We show that, before the reform, expected pairs trading returns incorporate a strong compensation for expected illiquidity. However, after the reform the required illiquidity compensation considerably decreases, denoting that investors perceived lower liquidity risk. Our findings help explain the pairs trading anomaly detailed in Gatev et al. (2006) and are consistent with Amihud (2002), extending to pairs trading the validity of his finding of a strong and positive relationship between expected returns and expected illiquidity. Nevertheless, we highlight that expected illiquidity cannot be regarded as the main driver of these expected profits: after the reform, expected pairs trading returns turn out to be higher, *(i)* reflecting reward to arbitrage, and *(ii)* incorporating a greater compensation for expected volatility.



[*]This is a solo-paper that I wrote during my PhD in the finance department at ESSEC. I am very grateful to Patrice Poncet, my dissertation advisor. This paper highly benefited from his valuable guidance and comments.

## 4.1 Motivation

According to financial theory, expected asset returns should incorporate, *ex ante*, a compensation for various types of risks. Among those, liquidity risk has been shown to be priced by the market: in his seminal work, Amihud (2002) reports that *"stock excess return, traditionally interpreted as a risk premium, includes a premium for illiquidity"*. The expected stock return should therefore include a compensation for the expected illiquidity, which represents a risk that the investor has to bear. In this paper, we investigate whether this holds as far as pairs trading strategies are concerned, *i.e.* we study whether investors require a compensation for expected illiquidity when deciding to implement the strategy.

We thus aim to shed light on the link between liquidity risk and pairs trading returns. We assess whether investors are concerned by the particular market regulation, in that they require a compensation for the liquidity risk that arises from the latter, which may potentially erase the returns of their statistical arbitrage strategy. As Goetzmann et al. (2006) point out in their seminal paper, the sources of the profitability of pairs trading are still a puzzling issue that is worth investigating. In this paper, we study whether the regulation of the market and its level of illiquidity may explain at least part of the returns stemming from this asset pricing anomaly.

Liquidity crucially depends on the market organization adopted: see, among others, Grossman et al. (1988). We here focus on market regulation and we run a natural experiment concerning a very specific regulatory change that was enforced in 2001 on the Italian stock market. We evaluate *(i)* whether market liquidity may be considered as a determinant of pairs trading returns, and *(ii)* if this change in market regulation, aiming at increasing market liquidity, can be considered effective, in that investors decrease the illiquidity compensation that they require *ex ante* to implement the strategy, given the more liquid market.

Traders' and investors' strategy returns depend on how liquid the traded assets are. The lower the liquidity, the riskier the strategy becomes, since the assets will be bought or sold facing higher liquidity costs, which may in turn erase the gross strategy returns. The expectation that investors have about future market illiquidity is therefore a crucial aspect to be taken into account when investigating statistical arbitrage strategies. Besides, this expectation depends on the perception that traders have about the effectiveness of such a reform aiming to increase market liquidity.

This liquidity issue is particularly relevant for pairs trading strategies, since they are always designed by focusing on pure statistical signals, mathematical rules and automated algorithms, which may however disregard a simple yet essential aspect affecting the potential strategy returns: how the market is organized and the effect of a particular market regulation on the payoff of the strategy. Moreover, pairs trading always hinges on two positions, one long and one short, therefore involving two transactions at the same time, which doubles liquidity costs and liquidity risk.

It is not the first time that liquidity is thought to be a key mechanism behind the existence of some famous asset pricing anomalies. Pastor et al. (2001) conclude their paper asserting that *"one direction for future research is to explore whether liquidity risk plays a role in various pricing anomalies in financial markets"*. They also suggest that momentum strategies, essentially the opposite of pairs trading, become less attractive when portfolio spreads based on liquidity risk are also available for investment.

In addition, as remarked by Avellaneda et al. (2010), pairs trading is one of the most famous and debated market anomalies and has widely been considered as "the ancestor" of statistical arbitrage strategies: it is one of the most famous zero-cost and self-financing strategies implemented by hedge funds and hinging on the purely statistical relationship linking two assets. The open issues of pairs trading have been so far constantly drawing the attention of the academic literature too: Krauss (2016) well investigates the different perspectives from which this point has been tackled, and we may also recall several recent attempts to shed more light on this topic, among which, for instance, Faff et al. (2016) and Bowen et al. (2016). Despite this, most questions about pairs trading still remain unanswered in the literature.

We run our analysis on the Italian stock market, which experienced in 2001 a reform that has been defined by Gleason et al. (2007) as *"a model that can be adapted by other* *stock exchanges to promote transparency and governance".* We will detail in the next sections the reasons why the Italian market presents some peculiar features making it a very specific and ideal setting to be investigated, but the core aspect of the reform is the following. A specialist is assigned to each stock listed in a newly created market segment, called STAR, in order to improve liquidity for some firms that are particularly important for the economy: more specifically, the specialist is obliged to intervene providing liquidity in case the bid-ask spread of a stock exceeds a predefined upper value. This latter boundary is discretionary fixed by the regulator in order to ensure that the bid-ask spread does not exceed a certain pre-determined value and that, accordingly, the market remains sufficiently liquid. In addition, firms listed in this market segment must abide by strict transparency and disclosure rules.

The specificity of this reform has attracted the attention of researchers, especially because of two main reasons. First, the Italian market presents some interesting differences with respect to the market regulation of the NYSE and NASDAQ, which will be described in Section 4.2. Second, and not less importantly, the change in market regulation enforced in 2001 was the only reform implemented at that time and no other relevant event took place: hence, the causal effect of such a reform can clearly be pinned down by investigating the behavior of the market before and after the reform. In this respect, Frino et al. (2008) analyze the Italian stock market before and after the regulation enforcement in 2001. The authors argue that the reform was effective in that it reduced the illiquidity thanks to the introduction of the obligation for the specialist to intervene as soon as the bid-ask spread would have crossed the upper threshold.

On the other hand, Perotti et al. (2010) claim that the average bid-ask spreads for the stocks that entered the STAR segment in 2001 were remarkably lower than the corresponding upper value set by the newly introduced regulation. Thus, the authors allege that the beneficial effects of the reform, if any, should be searched in the higher transparency duties imposed by the new regulation, among which, for instance, the obligation to publish twice per year reports about the firm and organize meetings with investors.

Hence, Perotti et al. (2010) assess whether this increase in information diffusion had an impact after the reform, concluding that *(i)* market-makers can be regarded as information providers, and *(ii)* the efficient aspect of the reform was the increased transparency instead of the improvement in liquidity given by the introduction of the specialists.

We aim to look at this reform from a different perspective: we evaluate whether market participants *perceived* the reform as effective, which is in itself a novel approach. In our framework, this translates into investigating whether investors required a significantly lower compensation for illiquidity risk after that the reform entered into force, since pairs traders would do so only if they perceived a reduced liquidity risk.

Furthermore, since the link between pairs trading returns, market regulation and liquidity risk has been largely overlooked so far, we contribute to the literature by showing that disregarding market regulation would lead to misinterpretations of the functioning of financial markets as well as of market participants' behavior. We provide evidence in favor of a large compensation for illiquidity risk required *ex ante* by investors who implemented pairs trading strategies before the reform. We show that the change in market regulation strongly influenced the behavior of these traders, since they perceived a much lower illiquidity risk and reduced the illiquidity compensation that they required after that the reform entered into force.

Moreover, we also aim to proceed in the path traced by the benchmark paper in the pairs trading field written by Gatev et al. (2006), who were the first to study the performance of the strategy and allege that assessing the underlying factor driving these pairs trading profits is a non-trivial issue and still represents an open and relevant research question. Thus, we investigate whether liquidity may help explain part of the pairs trading anomaly first put forward by Goetzmann et al. (2006), which is in itself a novel approach, and we identify the relative importance of liquidity risk and other types of risks reflected in these expected strategy returns.

Hence, the contribution of this paper is threefold. First, we show that a statistical arbitrage strategy as pairs trading is strongly affected by market illiquidity: there exists a positive and significant relationship, both economically and statistically, between expected returns and expected illiquidity. Second, this illiquidity compensation largely decreases after the reform was enforced, shedding light on the fact that investors perceived the reform as effective, *i.e.* they "priced" the reform. Third, we show nevertheless that liquidity cannot be considered the main driver of these pairs trading returns, since expected pairs returns mostly reflect an *ex-ante* compensation required by investors for the existence of volatility risk.

## 4.2 Related work

Starting from the seminal work by Gatev et al. (2006), much has been written on pairs trading strategies: among the most debated topics there are *(i)* how to enhance returns (Broussard et al. (2012), Lei et al. (2015)), *(ii)* the consistency of the performance over time (Do et al. (2010)), *(iii)* the mathematical modelling underlying these trading strategies (Tourin et al. (2013)), and *(iv)* the analysis of the determinants of its profitability in the US equity market (Jacobs et al. (2015)). Nevertheless, the extant literature has not covered two essential aspects of pairs trading: on the one hand, the underlying drivers of these returns, and, on the other hand, the impact of liquidity risk on these zero-cost self-financing portfolios.

In addition to the aforementioned papers by Amihud (2002) and Pastor et al. (2001), the positive relationship between expected returns and expected illiquidity has been much investigated in the literature. Acharya et al. (2005) argue that the required return of a security is positively correlated with its expected illiquidity, an empirically verified stylized fact that gives rise to a liquidity-adjusted CAPM. This finding vindicates the result obtained by Gibson et al. (2004), who allege that systematic liquidity risk is priced in the US.

Bekaert et al. (2007) study the link between liquidity and expected returns in emerging markets, concluding that market liquidity is an important driver of expected returns and that the liberalization process has not completely erased its impact. They claim that emerging markets are an ideal setting to evaluate the liquidity-return relationship because of the variation in liquidity experienced by those markets. We think that a natural experiment on a very specific change in market regulation aiming at increasing liquidity, as the one entered into force in Italy in 2001, represents a unique, clear and remarkably neat setting to assess whether changes or shocks to market liquidity impact expected returns.

The extant literature also provides wide evidence of the existence of time-varying liquidity premia as well as commonalities in liquidity, which clearly affect the return-liquidity relationship. Watanabe et al. (2008) report that liquidity premia as well as liquidity betas are time-varying and provide evidence of a conditional liquidity premium that is more than twice with respect to the value premium. Chordia et al. (2000) underscore how relevant it is to focus not only on attributes of single assets, but also on correlated movements in liquidity, reporting that quoted spreads, quoted depth and effective spreads co-move with market- and industry-wide liquidity.

Domowitz et al. (2005) separate liquidity commonalities from return commonalities, asserting that cross-sectional correlation in order types induces co-movements in demand and supply (market and limit orders), which in turn affects liquidity commonalities, whereas the main determinant in return commonalities is correlation in order flow (order direction and size). Karolyi et al. (2012) explore the same topic but at the international level, claiming that liquidity commonalities are greater in countries with and during times of high market volatility, more international investors and more correlated trading activity. Hasbrouck et al. (2001) show the existence of common factors, albeit relatively small, across different stocks for some liquidity proxies as the bid-ask spreads and the bid-ask quote sizes.

Moreover, Coughenour et al. (2004) argue that liquidity co-moves for those stocks handled by the same specialist firm. Liquidity commonalities reinforce the interest of assessing the impact of liquidity on pairs trading, since a shock in liquidity for a stock can also be experienced at the same time by another asset that co-moves with the former. This would double the liquidity risk for pairs traders who simultaneously invest in a long and a short position. In addition, it would also increase the probability that the gross returns of the strategy may be at least partly, if not fully, erased by these liquidity shocks.

The remainder of this paper is organized as follows. Section 4.3 details the relevant features of the Italian market on which we run our natural experiment, as well as our research design. Section 4.4 describes the data used. Section 4.5 presents all the empirical results, highlighting separately the different research questions to which we answer. Section 4.6 concludes.

## 4.3 The natural experiment

In April 2001 a market reform was introduced on the Italian stock market ”Borsa Italiana” (London Stock Exchange Group). Before 2001, liquid and illiquid stocks were both traded through an electronic auction market. Liquid stocks were continuously traded over an entire trading day, whereas illiquid stocks were traded in a parallel system for about half a trading day. From 2001 onwards, the two categories of stocks were replaced by three different market segments. The blue chips, *i.e.* those stocks with the highest market capitalization, required to be above 1 billion euros, were still traded on an electronic auction market. For those stocks that were not attaining that capitalization threshold, a different market segment was created, called SBO (”Segmento di Borsa Ordinario”, ”Ordinary Market Segment”), still based on a continuous electronic auction.

It is the third segment that turns out to be key for our purposes. It is called ”STAR (Segmento Titoli ad Alti Requisiti)”, the translation of which reads ”Segment for High Requirements Shares”. The STAR segment was dedicated to medium-sized companies which voluntarily adhered to and complied with the following requirements. First, unlike the Blue Chips, market capitalization must be comprised between 40 million and 1 billion euros. In addition, these stocks are required to have high liquidity in terms of free float: minimum 35% at the moment of entering the STAR, with the obligation of keeping it above 20% in order to remain in this segment. Furthermore, high transparency and disclosure must be guaranteed, as well as corporate governance in line with international standards, as, for instance, *(i)* presence of independent directors on the Board, *(ii)* internal committees established by the Board of Directors, and *(iii)* incentive compensation for the top management.

Most interestingly, in the STAR segment each security was assigned one specialist to control trading. The crucial aspect that has to be underscored is the following. All the orders for the stocks included in the STAR segment were not sent anymore to an electronic order book directly, but they were channeled to the specialist. The latter *controlled* the limit order book, and could either execute the order against her inventory or send it to the limit-order book. The detail that makes this setting particularly interesting is that, although most of the papers focus on the NYSE and NASDAQ, there is a substantial difference between these markets and the Italian STAR segment. As explained by Frino et al. (2008), the difference between the Italian STAR and the NYSE is that in the former the *single* authorized specialist *controls* the limit-order book and can decide either to execute the order against her inventory or to post it in the limit-order book, whereas in the NYSE *several* specialists *compete* with the limit-order book.

The purpose of the new regulation was to provide additional liquidity to the stocks included in the STAR market, since these stocks represented particularly important parts of the Italian economy. Hence, although the specialist in the Italian STAR segment has no privileged access to the limit-order book, she has to provide liquidity in terms of ensuring that the bid-ask spread is not larger than a pre-determined threshold. This threshold is varied according to the average trading volume and the quantity of orders.

### 4.3.1 First Channel: From Market Regulation to Market Liquidity

In this subsection we list the liquidity measures that we employ to evaluate the impact of the market reform on market liquidity. We analyze the *Bid-Ask Spread (BAS)*, defined as

$$BAS_t \equiv bid_t - ask_t \tag{4.1}$$

where both the bid and ask prices are at close of market.

We investigate the dynamics, before and after the reform, of the *Effective Spread (ES)*, which can be defined as

$$ES_t \equiv 2\, D_t\, (p_t - m_t)\,, \tag{4.2}$$

where $p_t$ represents the price of the security at time $t$,

$m_t \equiv \frac{bid_t + ask_t}{2}$,

and

$D_t$: binary variable that takes value $+1$ if the trade is buyer-initiated or $-1$ if it is seller-initiated. To determine the value of $D_t$, we apply the decision rule developed by Lee and Ready (1991).

The effective spread is our main variable of interest because it represents the effective liquidity cost that the investor has to bear, unlike the bid-ask spreads that describes the expected gain of the market-maker. Indeed, the effective spread takes into account the difference between the price at which the investors buys (sells) an asset and the midpoint of the bid-ask spread, with the latter being the theoretical price at which the investor would be able to buy (sell) that asset in a frictionless market. Since we focus on the liquidity cost faced by the investors, we put ourselves in the shoes of pairs traders and not in those of the market-makers, the effective spread turns out to be our key variable of interest.

We also study the *Covariance Spread Estimator (CSE)* developed by Roll (1984). It is defined as

$$CSE_{p,t} \equiv \begin{cases} 2\sqrt{-Cov\,(\Delta p_t, \Delta p_{t-1})}, & \text{if } Cov\,(\Delta p_t, \Delta p_{t-1}) < 0 \\ 0, & \text{if } Cov\,(\Delta p_t, \Delta p_{t-1}) \geq 0 \end{cases} \tag{4.3}$$

and it is another widely used measure to assess the level of liquidity in the market. Roll (1984) shows that *i)* this measure is consistent with the hypothesis of efficient markets, *ii)* it takes into account the fact that trading costs induce negative serial dependence in successive observed market price changes, and *iii)* it is empirically related to firm size.

We also look at the Amihud *Amihud Illiquidity Ratio (AIR)* developed by Amihud (2002). It is defined as

$$AIR_{j,m} \equiv \frac{1}{L_{j,m}} \sum_{t=1}^{L_{j,m}} \frac{\mid r_{j,t} \mid}{V_{j,t}} \tag{4.4}$$

where $\mid r_{j,t} \mid$ is the absolute value of return for stock $j$ at time $t$, $V_{j,t}$ is the trading volume for stock $j$ at time $t$ and $L_{j,m}$ represents the number of days used to average the ratio between absolute returns and trading volume. We choose $L_{j,m} = 30$ days for any stock because our natural experiment is run on a . This proxy of market illiquidity measures the price impact of trading, shedding light on the the effect on stock return given by trading volume. Needless to say, high values of this indicator signal lower liquidity, since, *ceteris paribus*, a given volume will have higher impact on stock return, meaning that the asset is illiquid.

An interesting measure that allows the researcher to proxy illiquidity simply from the time-series of stock returns is the *Lot Measure* developed by Lesmond et al. (1999). It is defined as the number of zero returns in the time-series at our disposal. The rational behind this liquidity measure is that when a stock displays many days with zero return, this highlights that many times it happened that there was no trading over an entire day. Accordingly, that stock is likely to display higher illiquidity. Lesmond et al. (1999) claim that their illiquidity proxy is particularly useful because it does not need any estimate of transaction costs, which are not easily available and, when available, they are cumbersome and expensive to purchase.
Moreover, we compute the *High-Low Spread Estimator (HLS)* developed by Corwin et al. (2012):

$$HLS_t \equiv \frac{2\left(e^{\alpha} - 1\right)}{1 + e^{\alpha}}, \tag{4.5}$$

where

$$\alpha \equiv \frac{\sqrt{4\,\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \frac{\gamma}{3 - 2\sqrt{2}}, \tag{4.6}$$

$$\gamma \equiv \ln \left[ \left( \frac{H^0_{t,t+1}}{L^0_{t,t+1}} \right) \right]^2, \tag{4.7}$$

$$\beta \equiv \frac{1}{2} \left\{ \sum_{j=0}^{1} \left[ \ln \left( \frac{H^0_{t,t+j}}{L^0_{t,t+j}} \right) \right] \right\}, \tag{4.8}$$

and $H^0_t$ $\equiv$ highest daily price at day $t$; $L^0_t$ $\equiv$ lowest daily price at day $t$; $H^0_{t,t+1}$ $\equiv$ $max\left(H^0_t, H^0_{t+1}\right)$; $L^0_{t,t+1} \equiv min\left(L^0_t, L^0_{t+1}\right)$.

According to Corwin et al. (2012), the highest and lowest prices observed at day $t$ are almost always, respectively, buy and sell orders. Hence, their difference can proxy for the bid-ask spread and the volatility observed at day $t$. As a consequence, the high-low spread estimator is also commonly used to measure volatility in addition to illiquidity.

### 4.3.2 Second Channel: From Market Liquidity to Pairs Trading Returns

In this subsection we analyze the impact of the reform on the relationship between expected strategy returns and expected illiquidity. Our main focus is to assess *(i)* whether expected illiquidity turns out to be an important determinant of expected returns, hence priced by investors, and *(ii)* if the reform significantly decreased the compensation for expected illiquidity required by pairs traders.

#### Pairs trading: strategy design and performance assessment

Let us denote by $r^A_t$ the return of asset $A$ at time $t$. We define the normalized price $\tilde{P}^A_t$ for stock $A$ at time $t$ as the theoretical price that a security would have when it started off from an initial, normalized, price of 1:

$$\tilde{P}_t^A \equiv \prod_{i=1}^{t} \left(1 + r_i^A\right). \tag{4.9}$$

Our key variable of interest is the difference in normalized prices for two assets, defined as

$$d_t^{A,B} \equiv \tilde{P}_t^A - \tilde{P}_t^B, \tag{4.10}$$

with mean $\mu_d^{A,B}$ and standard deviation $\sigma_d^{A,B}$.

Under the assumption that assets A and B co-move, $d_t^{A,B}$ will fluctuate around its mean. Therefore, we need to define a tunnel inside which the difference in normalized prices is expected to fluctuate most of the times. The corridor can be constructed as

$$c^{A,B} \equiv \left[\mu_d^{A,B} - k\,\sigma_d^{A,B}\;; \quad \mu_d^{A,B} + k\,\sigma_d^{A,B}\right] \tag{4.11}$$

for any positive constant $k$ that can be set arbitrarily. The parameters to build this corridor are computed over a *formation period*. Then, a *trading period* begins, during which the strategy is implemented. Each trading period always starts at the end of its correspondent formation period. We apply a rolling-window approach: the subsequent formation period is shifted over time such that its last day coincides with the last day of the previous trading period. In this fashion, we ensure that trading activity never gets interrupted.

The length of the formation period is always chosen to be greater than or equal to the length of the trading period, in order not to lose information. In this paper, we choose a 40-day formation period and a 20-day trading period. This choice is motivated by the fact that we select a period of analysis going from one year before to one year after the event. Hence, not to lose too much information and in order to have at our disposal a number of observations as large as possible for the panel regressions, we prefer to work with a relatively short formation period, and, accordingly, with a relatively short trading period as well. Accordingly, we set $k = 0.5$ to build the corridor, since in the short-term

$d_t^{A,B}$ is less likely to experience very big shocks, driving it far from its historical mean, followed by a reversion towards the equilibrium relationship. It is therefore natural to pair up short-term strategies with relatively narrow corridors to exploit the asset co-movements and enhance the strategy returns.

Once the corridor has been set up, the trading strategy can be implemented. As soon as $d_t^{A,B}$ steps out of the corridor, this signals a divergence in the difference between the normalized prices of the two assets. If these two securities co-move, they are anyway expected to revert back to their original relationship. This enables us to bet on this statistical pattern and to build on it the trading strategy illustrated in figure 1.

[ Insert Figure 4.1 Near Here ]

The strategy is triggered when either of the following two conditions is met.

1. $d_t^{A,B} > \mu_d^{A,B} + k\,\sigma_d^{A,B}$: as soon as $d_t^{A,B}$ crosses the upper threshold *from above*, a trading position is opened. Since asset A is overpriced with respect to asset B, the strategy is short A and long B.

2. $d_t^{A,B} < \mu_d^{A,B} - k\,\sigma_d^{A,B}$: as soon as $d_t^{A,B}$ crosses the lower threshold *from below*, a trading position is opened. Since asset A is underpriced with respect to asset B, the strategy is long A and short B.

Thus, we define the following indicator variable

$$I_t^{A,B} \equiv \begin{cases} 0, & \textit{not open} \\ +1, & \textit{short } A, \textit{ long } B \\ -1, & \textit{long } A, \textit{ short } B \end{cases} \tag{4.12}$$

so that the daily return for the pair formed by securities A and B, denoted by $r_t^{A,B}$, can be computed as

$$r_t^{A,B} = I_t^{A,B} \left( r_t^B - r_t^A \right). \tag{4.13}$$

The reader will notice that $I_t^{A,B}$ is only an indicator variable that is used here to clarify the computation of the daily return of a pair. However, it does not mean that the investor will buy and short-sell only one quantity of assets A and one of asset B. The number of securities bought and sold short are determined as a function of the relative price of asset A with respect to asset B, such that the resulting portfolio is self-financing. Therefore, there is no need to borrow at the risk-free rate. On the other hand, short-selling involves additional trading costs that will be taken into account in our empirical analysis.

In both scenarios, the positions are simultaneously closed as soon as, at time $t$, one of the following two conditions is satisfied.

1. $d_t^{A,B}$ reverts back and crosses $\mu_d^{A,B}$: the reversion towards the historical statistical relationship is completed and therefore a statistical-arbitrage profit is achieved.

2. $d_t^{A,B}$ does not revert to its mean: in this scenario, the difference in normalized prices would cross back the upper or lower threshold and would step out of the corridor accordingly, making the profit equal to zero.

In the second case, the arbitrageur would manage to close the positions in correspondence to the exact same value of the threshold at which she started the strategy. In this respect, it is worthwhile underscoring that working with daily closing prices, as in this simulation approach, would make it possible to realize losses that would be easily avoided on a real trading desk. In fact, $d_t^{A,B}$ may step out of the corridor *before* the end of the trading day: hence, we would suppose to close the positions at the end of the trading day, when $\mathrm{d}_t^{A,B}$ may have further diverged from the corridor. Furthermore, being $d_t^{A,B}$ a continuous time process, there is a small probability that $d_t^{A,B}$ might also be tangent from above (below) to the upper (lower) boundary, without actually stepping into the corridor, but diverging away. In that (very unlikely) scenario the positions would be opened anyway and would generate a loss. This never occurs in our sample for any pairs.

When computing the annualized returns of the strategy there is an issue that has to be taken care of. We deal with a zero-cost portfolio, hence the returns of the latter cannot be computed as in the traditional way, because of the division by zero that would lead to financially meaningless results. To solve this problem, we treat the long and short legs of the strategy as two different portfolios, cumulating separately their returns. Afterwards, we annualize these returns also separately. We consider the final annualized strategy return as the sum of the annualized returns of the long and short portfolios.

**Assessment of the relationship between expected illiquidity and expected returns**

After computing the returns of the strategy, we move to assessing whether market liquidity had an impact on these returns. For this purpose, we employ a set of panel regressions as follows. The dependent variable is represented by daily returns of the strategy for each pair. Usually, in asset pricing, excess returns are employed instead of returns. However, pairs trading returns are obviously excess returns by construction $(r_A - r_B)$. We stack in a column vector the daily returns of all possible pairs, one pair after another. Denoting by $P$ the total number of pairs in our sample, we stack all daily returns for pair $p$ below those of pair $p-1$, with $p = 2, 3, ..., P$.

To assess the impact of the illiquidity expected by investors on *ex ante* expected strategy returns we run an analysis in the spirit of Amihud (2002). As this is the seminal and benchmark paper on expected returns and expected illiquidity, we follow his approach and apply it to pairs trading. In our panel regressions, all our independent variables are at time $t-1$, while strategy returns are at time $t$. Conditional on the information observable up to time $t-1$, investors formulate their expectation of the market illiquidity that they will have to face at time $t$ in case their statistical arbitrage strategy will require to open or close the positions.

Investors can observe up to time $t-1$ the liquidity costs that they have borne so far. We aim to derive the illiquidity that these investors expect to face at day $t$ for each of the two stocks in a pair. As explained before, several measures have been proposed in the literature to proxy for illiquidity. In our framework, we analyze the stock illiquidity expected by the investors who perform a pairs trading strategy and who face the actual illiquidity costs stemming from the stocks included in those pairs that they trade. Consequently, the actual illiquidity cost that they face can be precisely quantified and accurately measured only by the effective spread, which is constructed on the actual difference between the price at which a transaction has been executed and the midpoint of the bid-ask spread, with the latter reflecting the price at which the trader could have bought (sold) the stock in a frictionless market. The effective spread is therefore the proper measure, from the investors' point of view, to describe the actual liquidity costs that these traders have faced up to time $t-1$.

The *ex ante* effect of market illiquidity on the pairs trading returns for any generic pair $p$ can be described as

$$\mathbb{E}\left[r_{t,p}\right] = \alpha_{0,p} + \alpha_{1,p}\, ILLIQ^{E}_{t,p}, \tag{4.14}$$

where $ILLIQ^{E}_{t,p}$ is the illiquidity cost that investors expect to face at time $t$ when implementing their pairs trading strategy. As mentioned before, our measure of illiquidity is represented by the percentage effective spread, obtained by dividing equation (1) by the midpoint $m_t$. Given that pairs trading opens and closes two positions in two different stocks at the same time, the liquidity costs that investors face are twice as much with respect to those of the strategies based on one single asset. Accordingly, our measure of illiquidity is chosen to be the average of the percentage effective spreads for the two stocks in the pair.

Investors can predict the liquidity costs they will have to face at time $t$ by observing the liquidity costs that they have faced up to time $t-1$. Amihud (2002) supposes that illiquidity follows an AR(1) process,

$$ILLIQ_{t,p} = \beta_{0,p} + \beta_{1,p}\, ILLIQ_{t-1,p} + \epsilon_{t,p}, \tag{4.15}$$

such that the expectation for the illiquidity at time $t$ conditional on the illiquidity observed up to $t-1$ that enriches the filtration $\mathcal{F}_{t-1}$, turns out to be

$$\mathbb{E}\left[ILLIQ_{t,p} \mid \mathcal{F}_{t-1}\right] = ILLIQ^{E}_{t,p} = \beta_{0,p} + \beta_{1,p}\, ILLIQ_{t-1,p}. \tag{4.16}$$

Plugging equation (4.16) into equation (4.14) we obtain

$$\mathbb{E}\left[r_{t,p}\right] = \gamma_{o,p} \, + \gamma_{1,p}\, ILLIQ_{t-1,p} + \nu_{t,p}, \tag{4.17}$$

where $\gamma_{0,p} = \alpha_{0,p} + \alpha_{1,p}\, \beta_{0,p}$ and $\gamma_{1,p} = \alpha_{1,p}\, \beta_{1,p}$.

We construct a panel by stacking the daily excess returns stemming from each pair in a column vector. We do the same for the illiquidity measure for each pair. In our panel regressions, we expect $\beta_1$ and $\gamma_1$ to be positive and statistically significant. If that were the case, *(i)* illiquidity would positively depend on the illiquidity level observed in the previous period, and *(ii)* expected strategy returns would be positively affected by expected illiquidity, with investors demanding a compensation for liquidity risk.

**The effects of the reform on the relationship between expected returns and expected illiquidity**

To address this issue, we add in our panel regressions the following two variables. We refer to *Dummy Experiment* as a binary variable that takes value 1 after that the reform entered into force and 0 before. Moreover, we define as *Target Variable* the interaction term which is the product between the expected illiquidity regressor and the dummy variable. It is our key variable of interest: if the reform did have an impact on the relationship between expected returns and expected illiquidity, this variable should be statistically significant. In that case, a negative sign is expected: an effective reform would improve liquidity, therefore leading investors to require a lower compensation for illiquidity risk after the reform entered into force.

**Identification of the main drivers of the expected strategy returns**

We estimate our panel regressions by adding some variables that could potentially affect the expected returns of the strategy. These variables also serve as controls in order to ensure the validity of our finding about the relationship between expected returns and expected illiquidity. Following Amihud (2002), these terms are lagged in order to explain the expected returns *ex ante*. Exactly as before, we stack all the values of every variable for each pair in a column vector, pair after pair. The regressors included are the following.

First, we control for strategy risk. We fit a NA-GARCH(1,1) process (non-linear and asymmetric GARCH) to the strategy returns to estimate their conditional volatility, in order to control for the risk of the strategy. To control for asset volatility, we use the average Parkinson volatility between the two stocks in the pair. The Parkinson volatility indicator $PV_{i,t}$ for stock $i$ at time $t$ is defined as

$$PV_{i,t} = \frac{1}{4\,\log 2}\left[\log(H_{i,t}) - \log(L_{i,t})\right]^2 \tag{4.18}$$

where $H_{i,t}$ and $L_{i,t}$ are the highest and lowest prices for stock $i$ at day $t$. We first compute the Parkinson volatility measure for each of the two stocks in the pair, and then we average these two values. These two aforementioned variables control for the risk embedded in the strategy and in the assets forming the pair. In addition, and intimately related to the previous point, they control for the hypothesis of reward to arbitrage: if the strategy returns were merely reflecting reward to arbitrage, controlling for the volatility should erase any other possible effect stemming from other factors.

We also control for the amount of trading through the sum of the volume turnover for the two stocks in each pair. The rationale is that excess returns after the reform may actually be driven not by the lower required compensation for illiquidity but by the higher trading volume due to the increased market liquidity. If this hypothesis were correct, controlling for trading volume would erase the significant effect conveyed by expected market illiquidity. Market capitalization is another aspect that we take care of: in this respect, we build a regressor as the average of the turnover in market value for the two assets in each pair. The turnover in market value is defined as the value of all trades for a stock on a particular day. This controls for the fact that we may be capturing some size effect.

Following Goetzmann et al. (2006) we employ their closeness index to describe the co-movements between the two stocks $i$ and $j$ forming pair $p$:

$$CI_{t,p} = \left(\tilde{P}_{i,t} - \tilde{P}_{j,t}\right)^2, \tag{4.19}$$

where $\tilde{P}_{i,t}$ defines the normalized price for stock $i$ at time $t$ as previously defined in equation (4.9). We control for the closeness index because another potential effect that we have to be careful about deals with the possibility that stocks co-moving more could happen to be simply those stocks with higher effective spreads. Investors would not demand a compensation for expected illiquidity but they would just face higher liquidity costs on those stocks that happen to co-move more, ensuring higher profits even taking into account their greater illiquidity. The closeness index is a measure of distance between the performance over time of two assets. We first estimate its first difference

$$\Delta CI_{p,t} = CI_{p,t} - CI_{p,t-1} \tag{4.20}$$

which measures if the two assets reduced or increased their distance between time $t-1$ and time $t$. When the strategy is open, the expected sign of its coefficient is negative: the strategy is expected to generate positive returns if and only if the two securities reduce their distance, which is what happens when they re-establish their statistical relationship after that a divergence occurred. As a second step, in the flavor of the procedure applied before, we estimate the expected co-movements at time $t$, conditional on the information available up to time $t-1$, for the two assets in pair $p$ by running the following regression

$$\Delta CI_{p,t} = \phi_{0,p} + \phi_{1,p}\,\Delta CI_{p,t-1} + \eta_{p,t} \tag{4.21}$$

and saving the predicted values $\mathbb{E}\left[\Delta CI_{p,t}\right] = \Delta CI^{E}_{p,t}$.

The rationale is always the same as before: conditional on the observed co-movements up to $t-1$, the investors estimate the co-movements of the two stocks at time $t$ and adjust their expectations accordingly. If they expect a reduction in the distance between the two stocks, they will expect higher returns from the strategy.

Hence, our complete panel regressions look like as follows:

$$
\begin{aligned}
r_{t,p} = \; & \gamma_{0,p} + \gamma_{1,p}\, ILLIQ_{t-1,p} + \gamma_{2,p}\, DUMMY_{t-1,p} \; + \\
& + \gamma_{3,p} \;\; ILLIQ_{t-1,p} \cdot DUMMY_{t-1,p} + \gamma_{4,p} \;\; \Delta CI^{E}_{p,t} \; + \\
& + \gamma_{5,p} \;\; STRATEGYRISK_{p,t-1} + \gamma_{6,p} \;\; ASSETVOLA_{p,t-1} \; + \\
& + \gamma_{7,p} \;\; VOLUME_{p,t-1} + \gamma_{8,p} \;\; VALUE_{p,t-1} + \nu_{t,p}.
\end{aligned}
\tag{4.22}
$$

We therefore expect two main results. First, and most importantly, $\gamma_3$ should exhibit a negative and statistically significant value. The interaction term would therefore signal a significant decrease in the compensation for illiquidity required *ex ante* by the investors and thus incorporated in expected pairs trading returns. Second, we expect the coefficient $\gamma_1$ to be positive and statistically significant. This result would extend to pairs trading the finding by *Amihud* of a positive and significant relationship between expected returns and expected illiquidity. All the other regressors represent control variables that are also useful to understand which additional factors may affect pairs trading returns.

## 4.4 Data

Our sample comprises the stocks that were already listed on the Italian stock market before the reform and that entered the STAR segment on April 2, 2001. We select all the stocks that were quoted in the Italian market Borsa Italiana (London Stock Exchange Group) with a traditional limit order book before April 2, 2001, our event date, and which then moved to the market segment STAR after the event day. We track 55 pairs for 515 days each, so as to form a panel comprising 28,325 observations. All the data used in this work have been downloaded from Datastream© and Bloomberg©. The simulations have been implemented in MATLAB© and STATA©.

For our natural experiment we need to define the pre-event and post-event periods. We may choose different time lengths, among which we select one year as the time-horizon for both the pre- and post-event periods. Furthermore, we leave few days before and after the event to accommodate for the transition. We define one trading week before and one after the reform as our transition period, disregarding from the analysis the days comprised in these two weeks. Our choice is motivated by the fact that we do not have many firms at our disposal, hence we opt for a slightly longer time period in order to increase the panel size. Accordingly, for the sake of consistency, we select two weeks and not only a couple of days as a transition period.

The pre-event period goes from Monday, April 3, 2000, to Friday, March 30, 2001, and comprises 260 observations for each stock. The post event period covers the time interval between Monday, April 9, 2001, and Friday, March 29, 2002, and is made of 255 data points. For the pairs trading strategy, in this paper we present the results referred to a 40-day formation period and a 20-day trading period. It therefore turns out that we run our regressions on a panel dataset comprising $22,000$ observations: 200 daily returns for each of the 55 pairs for the pre-reform period, plus 200 returns for the post-event period.

## 4.5 Empirical results

In this section we report the results of our analysis. Our main variables of interest are the illiquidity regressor and the interaction of the dummy variable for the pre- and post-event periods with the illiquidity variable. Regarding the expected illiquidity, we expect a positive and statistically significant sign if expected returns do incorporate a compensation for illiquidity risk. As far as the interaction term is concerned, we expect a negative and statistically significant sign: if a change in market regulation matters, controlling for reward to arbitrage, statistical co-movements between the stocks, trading volume and size effects should not erase the significant effect conveyed by the decrease in the required illiquidity compensation.

### 4.5.1 Assessment of the Pairs Trading Returns Before and After the Reform

Table 4.1 reports the results for the pairs trading returns before and after the reform, distinguishing between the long and short portfolio. Pairs trading returns turn out to be higher after the event: the mean of the annualized returns across all pairs is 33.12% after the reform against a value of 18.38% before the event. Not only pairs trading returns display a lower mean after the reform, but also a lower standard deviation, 16.76% after against 24.56% before. In addition, they become less leptokurtic: the kurtosis is 2.37 after the event against 3.10 before.

[ Insert Table 4.1 Near Here ]

We have conducted several simulations with different values of the threshold $k$ for the corridor and all the results are still consistent: pairs trading returns turn out to be higher after the reform. This sheds light on the fact that exploiting co-movements between pairs of securities has been more profitable after the reform irrespective of the value of $k$. Thus, stocks have co-moved more after the reform was enforced. Moreover, we test for the impact of transaction costs. We assume that traders face a cost equal to 0.20% at any transaction executed for the long portfolio, and the same for the short portfolio. Our results indicate that returns stay economically, and not only statistically, significant even when accounting for such a prudential estimate of the transaction costs. We are aware of the fact that, as far as a professional trader is concerned, 0.10% would represent more realistically the actual transaction costs borne. We nevertheless decided to run the simulations with transaction costs equal to 0.20% in order to adopt an approach that is as prudential as possible. We have been indeed able to show that pairs trading returns were still economically significant even with such a high level of transaction costs. This reinforces our message about the remarkable performance of these pairs strategies, especially when exploiting narrow short-term deviations from the equilibrium relationship.

This result creates a perfect environment to assess the impact of liquidity. In fact, one may suspect that if the reform were perceived as effective by investors, the required compensation for illiquidity would be lower after the event. This may in turn reduce the *ex ante* expected profits of the strategy. However, here pairs trading returns get enhanced after the reform. The next subsections investigate *(i)* whether the reform impacted the illiquidity compensation required by investors, and *(ii)* which are the main determinants that led to an increase of these strategy expected returns, despite the reduction that one may expect of the required illiquidity compensation.

As far as liquidity is concerned, we compute the mean value of each of the liquidity measures described in Section 2 before and after the event. Using a sample almost identical to ours, Frino et al. (2008) show that liquidity does improve after the event. To reinforce the point, we first sum the values of each liquidity measure for both stocks in each pair. Second, we average these values before and after the reform. Last, we count how many pairs experienced a decrease in the mean value for a particular liquidity measure after the reform.

Our results show that 38 pairs out of 55 experienced a decrease in the average effective spread after the reform. Furthermore, 42 pairs also display a reduction in the average bid-ask spread in the post-event period. As far as the covariance spread estimator is concerned, 29 couples display lower average values after the event. However, our results show that volatility increases after the reform, since for the high-low spread estimator, usually regarded as a measure of how volatile a stock is, only 11 pairs out of 55 experienced a decrease after the reform. The exact same information is conveyed by the lot measure. Overall, our results indicate that for most pairs the effective spread did decrease after the event, vindicating the findings in Frino et al. (2008). On the other hand, our analysis of the high-low spread estimator shows that higher volatility at the stock level is associated with most pairs after the reform, reinforcing the need of including a control variable for stock volatility, as we did in this study.

### 4.5.2 The Impact of Liquidity on Pairs Trading Returns

To start with, we investigate whether there is a relationship between *contemporaneous* returns and illiquidity. As far as single stocks are concerned, several papers have documented such effect: among others, Acharya et al. (2005), Martinez et al. (2005) and Lam et al. (2011). The extant literature has therefore shown the robustness of this finding over time and across countries, analyzing different time-periods and different stock markets. In this paper we focus on the return-illiquidity relationship but from a totally different perspective: we are interested in discovering if and how a statistical arbitrage strategy as pairs trading can be affected by liquidity risk and if the pairs trading anomaly can be explained by market illiquidity.

Table 4.2 reports the results for the regression of contemporaneous strategy returns on all the regressors, before and after the event. Before the reform, results confirm the well-known empirical evidence in asset pricing of a positive contemporaneous relationship between returns and illiquidity, as pointed out by Amihud (2002). The effective spread regressor has a positive sign with a $t$-stat equal to $2.99^{(***)}$. However, this relationship breaks down after the event, when a significant contemporaneous relationship does not exist anymore. This gives us the intuition that the reform did change the liquidity-returns relationship significantly.

[ Insert Table 4.2 Near Here ]

Table 4.2 also shows that, as expected, there is a negative and statistically significant relationship between strategy returns and asset co-movements: when the two securities in the pair co-move more, strategy returns are higher. The co-movement regressor displays a $t$-stat equal to $-4.18^{(***)}$ before the event and $-2.29^{(**)}$ after the reform. However, it is worthwhile recalling that these results have been obtained not deleting the zeros from the dependent variable. In fact, several strategy returns in our sample turn out to be equal to zero, since the pairs strategies do not open too often. Therefore, to have further insights on the return-illiquidity relationship, we *(i)* delete all the zero returns from the dependent variable, and *(ii)* we perform standard panel regressions as well as quantile regressions to check for any non-linearity in the data.

[ Insert Table 4.3 Near Here ]

Table 4.3 shows that, deleting all the zeros, illiquidity still displays a positive sign with $t$-stat $2.77^{(***)}$. Moreover, the interaction term is negative, as expected too, with a $t$-stat that equals $-2.18^{(**)}$. It is not surprising either that returns are strongly affected by asset volatility: the corresponding $t$-stat is $6.09^{(***)}$. Once more, the expected co-movements are strongly significant too, displaying a $t$-stat of $-4.15^{(***)}$. The well-known empirical evidence in asset pricing of a positive *contemporaneous* relationship between returns and illiquidity is therefore still confirmed. Furthermore, we can infer that the reform changed significantly this relationship: it aimed to increase liquidity, and indeed after the event the relationship between returns and illiquidity was strongly weakened.

In order to check for possible non-linearities in the relationship between contemporaneous returns and illiquidity, we move to run quantile regressions for several different quantiles. Our results reveal that *(i)* the contemporaneous relationship is very strong from quantile 65 to quantile 95, whereas it turns out to be weaker before. Illiquidity is strongly related to *positive* returns, whereas the relationship is weaker for negative returns. Moreover, for these quantiles, the interaction term is always negative and strongly significant, shedding light on the breakdown of the positive contemporaneous return-illiquidity relationship after the reform.

These results are intuitive: if the process we are dealing with is mean-reverting, after the positions have been opened the process should revert back to its mean, generating positive returns. Otherwise, strategy returns can be either zero, when the pair does not open and thus we do not deal with a mean-reverting process, or negative, when the pair does open but then the process re-diverges away from the mean, which is not what one would expect dealing with mean-reverting processes. Hence, our main focus should be on *positive* strategy returns, since we aim to explain the returns stemming from assets that co-move and are expected to generate positive returns, a necessary condition for the investors to decide to trade.

We now investigate whether *(i)* investors require *ex ante* an illiquidity compensation, *i.e.* there appears to be a positive relationship between expected returns and expected illiquidity, and *(ii)* this relationship breaks down after that the reform was enforced, since investors perceived the reform as effective in that they recognized a liquidity improvement that got reflected in a lower liquidity risk. The set of panel regressions presented from now onwards focus on the *expected* illiquidity that leads investors to demand *ex ante* a compensation for this risk, and on the *expected* strategy returns.

[ Insert Tables 4.4 to 4.9 Near Here ]

Tables 4.4 to 4.9 report the results for the quantile regressions before and after the event. It is noticeable that after the event the illiquidity variable is always strongly significant for the positive strategy returns. This sign is concordant with the finding of Amihud (2002). The coefficient of the expected liquidity is positive, confirming the existence of a compensation required by investors to implement the trading strategy. This compensation is required *ex ante* by traders because they have to bear liquidity risk. To measure the effect of this compensation on strategy returns it suffices to analyze the coefficient of the expected illiquidity regressor, which also shows that the coefficient is not only statistically significant, but also economically.

Let us take the results reported in Table 4.5 as an enlightening example. The coefficient of the expected illiquidity regressor displays a value equal to 0.188, which is easily interpretable as follows. Both excess returns and effective spreads are expressed in percentage points. Moreover, the expected illiquidity regressor is defined as the sum of the effective spreads of the two stocks in the pair. Hence, an increase of 1% in the illiquidity regressor means that an average increase of 0.50% in the expected illiquidity that investors estimate to face for each of the two securities in the pair translates into an increase of 0.19% for the returns that traders require *ex ante* and expect to get from the strategy. This effect is therefore economically very strong and is consistent across all estimations reported in all the aforementioned tables.

The next logical step is to ask ourselves whether there is a different impact of market liquidity on pairs trading returns before and after the reform. In the previous quantile regressions we showed that illiquidity was strongly priced after the reform, as expected. We also noticed a different behavior in the pre- and post-event periods. In what follows we investigate whether the interaction term between the dummy variable for the experiment and the illiquidity variable is significant or not.

[ Insert Table 4.10 Near Here ]

We present in Table 4.10 the results stemming from Tobit regressions. We aim to explain the *positive* expected returns of the strategy: in fact, pairs trading produces positive returns when the process studied is indeed mean-reverting and, once a divergence occurred, it regresses back to the mean of the corridor. Besides, most strategy returns in our sample turn out to be zero because the strategy never opens. Hence, in our sample we observe several zeros, even if they have nothing to do with the distribution of the true strategy returns when the strategy actually opens. One may be interested only in those cases when the pairs trading strategy is actually implemented, *i.e.* when the strategy is opened. If no mean-reverting process existed, pairs trading would never be implemented, making it meaningless to analyze the sources of its profitability, which would always be zero.

Accordingly, we run a Tobit regression left-censoring the dependent variable at zero. We therefore exploit the fact that the true distribution of the strategy returns, once a divergence occurred and $d_t^{A,B}$ jumps into the corridor, is different from the returns distribution that we observe in our sample. Results are presented in Table 4.10. The illiquidity coefficient is statistically significant at the 1% level, with a $t$-stat equal to $3.24^{(***)}$. Moreover, the interaction term turns out to be negative and significant, displaying a $t$-stat of $-2.88^{(***)}$. Therefore, we can conclude that *(i)* the former result highlights the existence of a strong relationship between expected returns and expected illiquidity, extending to pairs trading the general result of *Amihud (2002)*, and *(ii)* the latter finding reveals that investors drastically reduced the required compensation for illiquidity incorporated in their expected pairs trading returns because of the improvement in liquidity after the enforcement of the reform.

The last issue to be considered, but not the least important, is to analyse if liquidity can be considered the only significant determinant of expected pairs trading returns. In other words, we aim to understand if these short-term divergences at the stock level are only due to expected temporary liquidity shocks in the two assets that lead their prices to diverge from the mutual equilibrium relationship, or if there are other explanatory factors that are worth considering.

Our findings reveal that liquidity cannot be considered the only driver of the pairs trading profits. If compensation for illiquidity were the only driver of pairs trading returns we should not observe any other significant variable. However, volatility is always the most economically and statistically significant regressor, displaying the highest coefficients (in absolute value) and $t$-stats. For instance, Table 4.10 confirms that the strategy volatility has a $t$-stat reaching $10.68^{(***)}$.

These results show that *(i)* a significant compensation for expected illiquidity is required *ex ante* by investors performing the pairs trading strategy, and *(ii)* a significant reduction of this compensation is observed after the reform was enforced. Both findings robust to the presence among the control variables of the strategy risk (volatility of the strategy returns) and of the volatility of each of the single assets in a pair. Our findings reveal that higher volatility is associated with most pairs after the reform. Volatility therefore plays a crucial role in affecting strategy returns, despite it does not erase the significant effect conveyed by the reduced compensation for illiquidity required *ex ante* by the investors. This result is not surprising, since volatility is a measure of risk. The higher the *expected* volatility, the higher the risk, and therefore the higher the *expected* returns: investors incorporate this higher risk into their expected strategy returns.

### 4.5.3 Robustness checks

To ensure the robustness of our findings, we perform a series of robustness tests. To start with, one may argue that the breakdown of the return-illiquidity relationship is not observed exclusively for the stocks subject to the market reform, but that an underlying factor affecting the whole universe of securities listed on the Italian stock market may be driving the results. Accordingly, we run the exact same analysis on a sample of control stocks, on which we should find the same results as before if the aforementioned hypothesis were correct. The matching procedure is performed as in Rindi et al. (2010), following the approach developed by Huang and Stoll (1996). Our results show that the interaction term is never significant, neither for *(i)* standard panel regressions, nor for *(ii)* quantile regressions (tested with several different quantiles), nor for *(iii)* truncated and Tobit regressions.

The Tobit regression supposes that there is a latent unobservable vector $y_t^*$, which linearly depends on an observable vector $\boldsymbol{x_t}$ through a parameter vector $\boldsymbol{\beta}$. In addition, there is an observable variable $y_t$ which is defined to be equal to the unobservable variable when the latter has values greater than zero, and it otherwise gets value zero. These relationships are described by the following equations,

$$y_t = \begin{cases} y_t^*, & if \quad y_t^* > 0 \\ 0, & if \quad y_t^* \leq 0 \end{cases} \tag{4.23}$$

$$y_t = \boldsymbol{\beta}\,\boldsymbol{x_i} + u_i, \;\; u_i \sim \mathcal{N}\left(0, \sigma^2\right) \tag{4.24}$$

which make clear why this model fits well with the situation we are describing. The unobservable variable is represented by investors' expectations. Needless to say, these expectations cannot be directly observable on the market, yet they will be reflected in the strategy returns because the investors will decide to trade or not to trade according to their expectations about the strategy performance. All that we can observe are the returns that the pairs trading strategy yields. The investors will face either of the following two situations. If they *ex ante* expect that the strategy will generate positive returns, they will trade. In this scenario, their expectation of their payoff will stay the same (positive). If, however, they *ex ante* expect negative strategy returns, they will obviously decide not to trade: accordingly, their expectation about their payoff from the pairs trading strategy will be zero, since no trade will occur.

In the truncated regression with zero as threshold, the illiquidity variable has a $t$-stat equal to $5.13^{(***)}$, whereas the interaction term is not significant, displaying a $t$-stat of 0.86. Moreover, the sign of the interaction coefficient is even positive instead of negative, contradicting the hypothesis that after the event the required compensation for illiquidity decreased. On the contrary, it still holds true that *(i)* volatility plays a crucial role in explaining strategy returns, and *(ii)* pairs trading returns turn out to be higher in the period after the event.

Moreover, we run Tobit censored regressions by modifying the threshold at which the data are censored. We progressively include more and more negative values, allowing the strategy to produce negative returns.

[ Insert Tables 4.11 to 4.13 Near Here ]

Tables 4.11, 4.12 and 4.13 report the results for several different levels of the threshold. As it can be inferred from these tables, *(i)* expected illiquidity still has a positive and strongly significant impact on the expected strategy returns, *(ii)* the interaction term is again negative and significant, hence the required compensation for the illiquidity is highly reduced after that the reform entered into force, and *(iii)* volatility plays the most relevant role, both from an economic and statistical point of view.

Instead of censoring the data at some predefined thresholds, we run a truncated panel regression using the same thresholds as before. Truncating the dependent variable at zero means that we delete all the strategy returns that are lower or equal to zero. On the other hand, when censoring, these latter returns are all set equal to zero. The (slight) difference is that when truncating we literally only analyze the positive returns of the strategy, deleting all the others; when censoring, instead, we implicitly assume that an investor will expect a strictly positive payoff from the strategy when the latter is open, given that she is dealing with mean-reverting processes and since we set to zero those expected returns that in our sample turn out to be negative or zero. If she expected negative returns in the subsequent day, the investor may decide not to trade, expecting accordingly a strategy return equal to zero given the absence of trading.

[ Insert Table 4.14 Near Here ]

Table 4.14 shows that when left-truncating all the zero returns by using zero as our threshold, the *t*-stat of the expected illiquidity becomes equal to $2.92^{(***)}$. In addition, the interaction term displays a *t*-stat of $-2.66^{(***)}$, confirming the validity of the results obtained before.

Another issue that is worthwhile investigating is whether more or less illiquid stocks have the same or a different impact on the pairs trading returns. In other words, we aim to identify whether the *level* of the stock illiquidity plays a relevant role in affecting the expected strategy returns. The rationale is that investors may expect lower strategy returns when facing higher expected liquidity costs, and *vice versa*. Indeed, proceeding along the same path, Nimalendran et al. (2003) shows that very illiquid stocks benefit more from the adoption of a market structure that increases liquidity than moderately illiquid assets. Hence, we run a spline panel regression dividing the expected illiquidity into 3 different group according to the 3 equally-spaced percentiles of its distribution.

[ Insert Table 4.15 Near Here ]

Table 4.15 reports the results and shows that the third group, *i.e.* the one comprising the pairs with the highest illiquidity, explains most of the results: its *t*-stat equals $3.43^{(***)}$, with an interaction term displaying a *t*-stat of $-3.05^{(***)}$. These findings thus confirm the stylized fact described by Nimalendran et al. (2003).

One may argue that illiquidity is also affected by asset volatility, as argued by Copeland et al. (1983). Hence, the coefficient of the expected illiquidity may simply be loading on a volatility effect. To neatly disentangle these two effects, we repeat the same analysis but in two main steps. First, we regress the effective spreads on the average asset volatility, and we save the residuals, *i.e.* the part of the effective spreads that is not explained by volatility. Second, we run our panel regressions exactly as before but employing the new illiquidity measure estimated in step 1. In this fashion, we clearly disentangle the impact of liquidity from that of volatility. Results do not change: both illiquidity and volatility remain significant at the 1% confidence level, with the same coefficient sign.

As mentioned before, Amihud (2002) models illiquidity by means of an AR(1) process. In order to follow his approach, we have also obtained our results under this (reasonable) assumption. Nevertheless, to convince the reader further about the robustness of our findings, we run the same analysis but progressively including more lags for the volatility specification. We test if results change when volatility is modeled as a more general AR(p) process with several different values for $p$. We find that the interpretation of our results does not change significantly, corroborating the robustness of our findings. Moreover, as expected, the first lag appears to be the most significant in explaining the volatility, with the other lags displaying a decreasing importance as $p$ increases.

To further disentangle the impact of the zero returns in our sample, we run a panel Probit regression transforming our observed strategy returns in a binary variable taking value 1 if the returns are greater than zero, or 0 otherwise. In addition, we also run a multinomial Logit regression where our dependent variable can take three different values: 0 if the strategy returns are 0, 1 if they are positive and 2 if they are negative. The rationale is that we aim to investigate whether the expected illiquidity may affect the probability that the strategy generates positive returns. Tables 4.16 and 4.17 report the results.

[ Insert Tables 4.16 and 4.17 Near Here ]

In Table 4.16 the illiquidity variable has a $t$-stat of $2.94^{(***)}$, and, as far as the interaction term is concerned, its $t$-stat is $-2.30^{(**)}$. The same message is conveyed by Table 4.17, where in the multinomial Logit regression with 0 (the zero returns) as basis, the $t$-stat for the illiquidity variable referred to the positive returns becomes $2.74^{(***)}$, and that of the interaction term turns out to be $-2.20^{(**)}$.

## 4.6 Concluding remarks

In this paper we have investigated the relationship between expected returns and expected illiquidity for pairs trading strategies. We have focused on a reform enforced in the Italian stock market in 2001. This reform introduced very *ad hoc* rules making this setting very specific and particularly interesting to evaluate how a change in market regulation impacts trading strategies implemented in that market. A new market segment, called STAR ("Segment for High Requirements Shares"), was introduced. Stocks listed in this segment were assigned a unique specialist who was supposed to *control* the limit order book, unlike in the NYSE where multiple specialists *compete* with the limit order book.

The reform aimed to increase liquidity for those stocks that entered the STAR segment. Most importantly, we have focused on how investors implementing pairs trading strategies perceived this reform as a means to evaluate the effectiveness of the latter. The reform was effective in that the compensation required *ex ante* by investors for the expected illiquidity significantly decreased after the reform.

Traders performing the strategy face illiquidity costs in the form of effective spreads, since the prices at which they execute their transactions do not coincide with the midpoint of the bid-ask spread, with the latter representing the price at which they could trade in a frictionless market. Therefore, the expected illiquidity has been defined as the expectation that investors form about the effective spreads that will prevail in the market at time $t+1$, conditional on the observable effective spreads up to time $t$, which are indeed the liquidity costs that investors had faced so far. To derive the expected illiquidity, we have followed the model by Amihud (2002).

First, we have run panel regressions confirming the strong positive relationship between contemporaneous returns and illiquidity, extending this famous stylized fact in asset pricing to pairs trading. Second, we have regressed expected strategy excess returns for every pair on the average expected illiquidity of the two stocks in each pair running an analysis in the spirit of Amihud (2002). Overall, our results confirm the positive and statistically significant relationship between expected returns and expected illiquidity which was documented by Amihud (2002) with reference to excess returns for individual stocks in the US market.

Interestingly, this expected illiquidity has a much lower impact after the reform, since the interaction term between the expected illiquidity and the dummy variable indicating the pre- and post-event periods is negative and statistically significant. We have shown that after the reform expected strategy returns were incorporating a much lower compensation for expected illiquidity. This finding sheds light not only on the fact that liquidity plays a relevant role in driving these expected strategy returns, but it also highlights that the reform was actually perceived as effective by the investors, who demanded a lower compensation for illiquidity risk.

Although the compensation for the expected illiquidity risk strongly decreased after that the reform was enforced, the strategy excess returns turned out to be higher after the event. This empirical evidence has made this setting even more interesting to assess *(i)* which are the main factors affecting the expected returns of the strategy and *(ii)* which variables generate an increase in expected returns even when accounting for the reduction in the required compensation for the illiquidity risk.

Proceeding along the same path, we have moved to further identify the additional determinants of the pairs trading returns, complementing the extant literature to help explain this asset pricing anomaly at the stock level. We have controlled for the expected co-movements between the two stocks in each pair by means of the expected first differences in the closeness index, the indicator proposed by Goetzmann et al. (2006) to compute how closely two securities co-move. As expected, we have shown that investors bet on the pure statistical mean-reverting relationship between the two assets in the pair, since the first difference in the expected distance between the two securities has a statistically significant impact on both the expected and the contemporaneous strategy returns.

Overall, this paper has shown that *(i)* there is a statistically significant relationship between contemporaneous pairs trading returns and illiquidity, which is consistent with the general belief in asset pricing, *(ii)* the relationship is also positive and statistically significant between expected returns and expected illiquidity, as found by Amihud (2002), *(iii)* after the reform was enforced, the improvement in liquidity was associated with a lower compensation for illiquidity required by investors, which signals that traders are concerned by the particular market regulation and that therefore the latter should not be neglected when studying statistical arbitrage strategies, and *(iv)* despite the decrease in the required compensation for illiquidity, after the reform pairs trading returns are higher since they mostly depend on expected asset volatility and reflect reward to arbitrage.

## 4.7 Appendix

Table 4.1: Strategy excess returns of the pairs trading strategy: descriptive statistics. For each of the 55 we compute the annualized returns of the short and right leg of the strategy as well as the total portfolio returns. In this table we report the descriptive statistics referred to the 55 annualized returns, one for each pair. *Before* and *After* refer to the pre- and post-event periods with respect to April 2, 2001, when the reform entered into force in the Italian stock market.

| | Long Ptf | | Short Ptf | | Total Ptf | |
|---|---|---|---|---|---|---|
| | Before | After | Before | After | Before | After |
| Mean | 13.18% | 14.73% | 11.38% | 18.38% | 24.56% | 33.12% |
| StDev | 12.21% | 9.88% | 11.13% | 11.52% | 20.14% | 16.73% |
| Skewness | 1.11 | 0.07 | 0.43 | 0.55 | 0.73 | 0.10 |
| Kurtosis | 4.40 | 2.01 | 2.05 | 2.84 | 3.10 | 2.37 |
| Median | 10.97% | 13.56% | 9.46% | 16.27% | 21.03% | 32.13% |
| VAR 5% | 0.00% | -1.44% | -1.16% | 3.79% | 0.00% | 10.24% |
| VAR 1% | -5.05% | -3.63% | -8.19% | -3.24% | -1.99% | -3.58% |

Table 4.2: **Contemporaneous** regression of daily pairs trading returns on the illiquidity variable plus the control variables. The illiquidity measure is the sum of the percentage effective spreads of the two stocks in the pair. *Dummy* takes value if after the reform and 0 before the event. *Interaction* is the product between illiquidity and the dummy variable. *Asset vola* is the average of the volatilities of the two stocks in the pair. *Strategy vola* is the volatility of he strategy returns, whereas *Volume* represents the sum of the volume turnover in the two stocks. *Value* is the absolute value of the difference of the turnover in market value for the two stocks in the pair. *"Co-movement"* is the expected variation in the closeness index, as discussed in Section 2. These results have been obtained by deleting all the zero strategy returns. Standard errors are robust. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | **Coefficient** | **t-Stat** | |
|---|---|---|---|
| Illiquidity | 0.180 | 2.77 | (***) |
| Dummy | 0.005 | 2.45 | (**) |
| Interaction | -0.170 | -2.18 | (**) |
| Asset vola | 5.205 | 6.09 | (***) |
| Strategy vola | -0.529 | -5.51 | (***) |
| Value | 0.000 | 1.24 | |
| Volume | 0.000 | 0.48 | |
| Co-movement | -0.165 | -4.15 | (***) |
| Constant | 0.011 | 4.92 | (***) |

Table 4.3: **Contemporaneous** regression of daily pairs trading returns on the illiquidity variable plus the control variables. The illiquidity measure is the sum of the percentage effective spreads of the two stocks in the pair. *Dummy* takes value if after the reform and 0 before the event. *Interaction* is the product between illiquidity and the dummy variable. *Asset vola* is the average of the volatilities of the two stocks in the pair. *Strategy vola* is the volatility of he strategy returns, whereas *Volume* represents the sum of the volume turnover in the two stocks. *Value* is the absolute value of the difference of the turnover in market value for the two stocks in the pair. *"Co-movement"* is the expected variation in the closeness index, as discussed in Section 2. **These results have been obtained keeping all values of the dependent variable, *i.e.* not deleting any of the zero strategy returns**. Standard errors are robust. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Before the reform | | | After the reform | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.044 | 2.99 | (***) | -0.002 | -0.39 | |
| Asset vola | 1.192 | 1.84 | (*) | 1.166 | 4.96 | (***) |
| Strategy vola | 0.041 | 1.31 | | 0.020 | 0.65 | |
| Value | 0.000 | 2.42 | (**) | 0.000 | 0.59 | |
| Volume | 0.000 | -2.08 | (**) | 0.000 | -0.39 | |
| Co-movement | -0.018 | -4.18 | (***) | -0.013 | -2.29 | (**) |
| Constant | 0.000 | -0.21 | | 0.001 | 2.31 | (**) |

Table 4.4: Quantile regression referred to the 95th quantile. All of the zero strategy returns have been deleted. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Before the reform | | | After the reform | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.138 | 2.34 | (***) | 0.028 | 0.29 | |
| Asset vola | -2.071 | -1.45 | | 9.332 | 8.08 | (***) |
| Strategy vola | 0.146 | 1.01 | | -0.169 | -0.81 | |
| Value | 0.000 | -0.27 | | 0.000 | 2.11 | (**) |
| Volume | 0.000 | 0.75 | | 0.000 | 0.67 | |
| Co-movement | -1.374 | -2.92 | (***) | 6.272 | 0.88 | |
| Constant | 0.055 | 15.41 | (***) | 0.047 | 10.57 | (***) |

Table 4.5: Quantile regression referred to the 90th quantile. All of the zero strategy returns have been deleted. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Before the reform | | | After the reform | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.188 | 3.04 | (***) | -0.015 | -0.55 | |
| Asset vola | -0.182 | -0.17 | | 7.585 | 3.61 | (***) |
| Strategy vola | 0.186 | 0.97 | | 0.164 | 2.07 | (**) |
| Value | 0.000 | -0.16 | | 0.000 | 0.83 | |
| Volume | 0.000 | 0.82 | | 0.000 | 0.26 | |
| Co-movement | -1.464 | -2.60 | (***) | 2.666 | 0.52 | |
| Constant | 0.037 | 10.21 | (***) | 0.035 | 14.38 | (***) |

Table 4.6: Quantile regression referred to the 85th quantile. All of the zero strategy returns have been deleted. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Before the reform | | | After the reform | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.163 | 1.79 | (*) | -0.036 | -0.74 | |
| Asset vola | 2.325 | 1.76 | (*) | 7.297 | 6.22 | (***) |
| Strategy vola | 0.099 | 0.80 | | 0.191 | 1.34 | |
| Value | 0.000 | -0.14 | | 0.000 | 1.47 | |
| Volume | 0.000 | 0.91 | | 0.000 | 0.75 | |
| Co-movement | -1.406 | -3.60 | (***) | 1.208 | 0.30 | |
| Constant | 0.030 | 10.88 | (***) | 0.029 | 11.71 | (***) |

Table 4.7: Quantile regression referred to the 75th quantile. All of the zero strategy returns have been deleted. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Before the reform | | | After the reform | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.124 | 1.88 | (*) | -0.015 | -0.38 | |
| Asset vola | 2.485 | 2.59 | (***) | 5.728 | 4.93 | (***) |
| Strategy vola | 0.072 | 0.65 | | 0.048 | 0.38 | |
| Value | 0.000 | -0.65 | | 0.000 | 0.91 | |
| Volume | 0.000 | 1.61 | | 0.000 | 2.08 | (**) |
| Co-movement | -1.046 | -2.77 | (***) | -0.238 | -0.62 | |
| Constant | 0.021 | 10.07 | (***) | 0.021 | 10.6 | (***) |

Table 4.8: Quantile regression referred to the 60th quantile. All of the zero strategy returns have been deleted. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Before the reform | | | After the reform | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.107 | 2.05 | (**) | -0.016 | -0.57 | |
| Asset vola | 2.124 | 1.74 | (*) | 3.552 | 5.38 | (***) |
| Strategy vola | -0.142 | -1.47 | | -0.031 | -0.36 | |
| Value | 0.000 | -9.26 | (***) | 0.000 | -0.73 | |
| Volume | 0.000 | 2.42 | (**) | 0.000 | 1.97 | (**) |
| Co-movement | -0.750 | -2.45 | (**) | -0.137 | -0.03 | |
| Constant | 0.015 | 8.89 | (***) | 0.016 | 8.98 | (***) |

Table 4.9: Quantile regression referred to the 45th quantile. All of the zero strategy returns have been deleted. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Before the reform | | | After the reform | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.088 | 1.84 | (*) | 0.004 | 0.22 | |
| Asset vola | -0.018 | -0.01 | | 2.846 | 4.00 | (***) |
| Strategy vola | -0.121 | -1.06 | | -0.045 | -0.44 | |
| Value | 0.000 | -3.85 | (***) | 0.000 | 0.71 | |
| Volume | 0.000 | 1.19 | | 0.000 | 0.48 | |
| Co-movement | -0.757 | -3.86 | (***) | -0.022 | -0.01 | |
| Constant | 0.010 | 5.43 | (***) | 0.009 | 4.79 | (***) |

Table 4.10: Panel Tobit regression of strategy excess returns on all the regressors explained in Section 2. The dependent variable is left-censored with threshold at 0, *i.e.* we exclude all those strategy returns that are lower or equal to zero. Standard errors are robust. We bootstrap the standard errors to make sure that results are robust. For the description of all the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Coeff | t-Stat | |
|---|---|---|---|
| Illiquidity | 0.491 | 3.24 | (***) |
| Dummy | 0.004 | 1.88 | (*) |
| Interaction | -0.470 | -2.88 | (***) |
| Asset vola | 1.571 | 0.51 | |
| Strategy vola | 0.978 | 10.68 | (***) |
| Value | 0.000 | -0.45 | |
| Volume | 0.000 | -2.21 | (**) |
| Co-movement | -0.115 | -0.45 | |
| Constant | -0.081 | -1.07 | |

Table 4.11: Panel Tobit regression with different thresholds. $ll(x)$ denotes the level $x$ at which strategy returns are left-censored. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | ll(-0.005) | | | ll(-0.01) | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.031 | 3.40 | (***) | 0.029 | 3.14 | (***) |
| Dummy | 0.001 | 2.26 | (**) | 0.001 | 2.17 | (**) |
| Interaction | -0.030 | -2.94 | (***) | -0.029 | -2.80 | (***) |
| Asset vola | 1.601 | 6.21 | (***) | 1.603 | 6.17 | (***) |
| Strategy vola | 0.104 | 9.21 | (***) | 0.099 | 8.72 | (***) |
| Value | 0.000 | -0.96 | | 0.000 | -1.11 | |
| Volume | 0.000 | -1.95 | | 0.000 | -1.81 | (*) |
| Co-movement | -0.036 | -1.37 | | -0.037 | -1.39 | |
| Constant | 0.000 | 0.01 | | 0.000 | 0.08 | |

Table 4.12: Panel Tobit regression with different thresholds. $ll(x)$ denotes the level $x$ at which strategy returns are left-censored. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | ll(-0.015) | | | ll(-0.02) | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.027 | 2.85 | (***) | 0.024 | 2.57 | (***) |
| Dummy | 0.001 | 2.04 | (**) | 0.001 | 1.96 | (**) |
| Interaction | -0.027 | -2.59 | (***) | -0.026 | -2.39 | (**) |
| Asset vola | 1.618 | 6.16 | (***) | 1.614 | 6.09 | (***) |
| Strategy vola | 0.095 | 8.26 | (***) | 0.091 | 7.86 | (***) |
| Value | 0.000 | -1.31 | | 0.000 | -1.52 | |
| Volume | 0.000 | -1.69 | (*) | 0.000 | -1.59 | |
| Co-movement | -0.038 | -1.40 | | -0.038 | -1.39 | |
| Constant | 0.000 | 0.12 | | 0.000 | 0.22 | |

Table 4.13: Panel Tobit regression with different thresholds. $ll(x)$ denotes the level $x$ at which strategy returns are left-censored. Standard errors are robust. For all the details about the variables, please refer to Section 2. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | ll(-0.03) | | | ll(-0.04) | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 0.022 | 2.27 | (**) | 0.020 | 2.02 | (**) |
| Dummy | 0.001 | 1.90 | (*) | 0.001 | 1.81 | (**) |
| Interaction | -0.024 | -2.22 | (**) | -0.023 | -2.06 | (**) |
| Asset vola | 1.601 | 5.92 | (***) | 1.574 | 5.74 | (***) |
| Strategy vola | 0.085 | 7.23 | (***) | 0.081 | 6.80 | (***) |
| Value | 0.000 | -1.57 | | 0.000 | -1.60 | |
| Volume | 0.000 | -1.50 | | 0.000 | -1.48 | |
| Co-movement | -0.037 | -1.33 | | -0.037 | -1.30 | |
| Constant | 0.000 | 0.30 | | 0.000 | 0.49 | |

Table 4.14: Truncated regression of strategy excess returns on all the regressors explained in Section 2. The dependent variable is left-truncated with threshold at 0, *i.e.* we exclude all those strategy returns that are lower or equal to zero. Standard errors are clustered by pair. For the description of all the variables, please refer to Section 2. In this specification, we use the expected illiquidity, defined as the part of the illiquidity explained by its previous values in the last three periods, instead of the illiquidity lagged once. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Coeff | t-Stat | |
|---|---|---|---|
| Illiquidity exp | 1.145 | 2.92 | (***) |
| Dummy | 0.028 | 2.49 | (**) |
| Interaction | -1.254 | -2.66 | (***) |
| Asset vola | 13.885 | 6.97 | (***) |
| Strategy vola | -0.054 | -0.46 | |
| Value | 0.000 | 0.82 | |
| Volume | 0.000 | 2.31 | (**) |
| Co-movement | -1.942 | -4.94 | (***) |
| Constant | -0.050 | -3.05 | (***) |

Table 4.15: Panel spline regression of strategy excess returns on all the regressors explained in Section 2. The illiquidity variable is subdivided into three different regressors by means of a linear spline. *Spline 1* refers to the strategy returns up to quantile 33 of the return distribution. *Spline 2* refers to the strategy returns from quantile 33 to 66. *Spline 3* refers to the strategy returns from quantile 66 onwards. The three interaction variables are the product of each of the aforementioned spline variables with the dummy variable. Standard errors are robust. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Coeff | t-Stat | |
|---|---|---|---|
| Spline 1 | 0.07 | 0.18 | |
| Spline 2 | -0.08 | -0.28 | |
| Spline 3 | 0.31 | 3.43 | (***) |
| Dummy | 0.00 | 0.45 | |
| Interaction 1 | -0.38 | -0.73 | |
| Interaction 2 | 0.41 | 1.04 | |
| Interaction 3 | -0.30 | -3.05 | (***) |
| Asset vola | 0.90 | 1.79 | (*) |
| Strategy vola | 0.99 | 13.30 | (***) |
| Value | 0.00 | -0.53 | |
| Volume | 0.00 | -3.59 | (***) |
| Co-movements | -0.04 | -0.20 | |
| Constant | -0.08 | -17.35 | (***) |

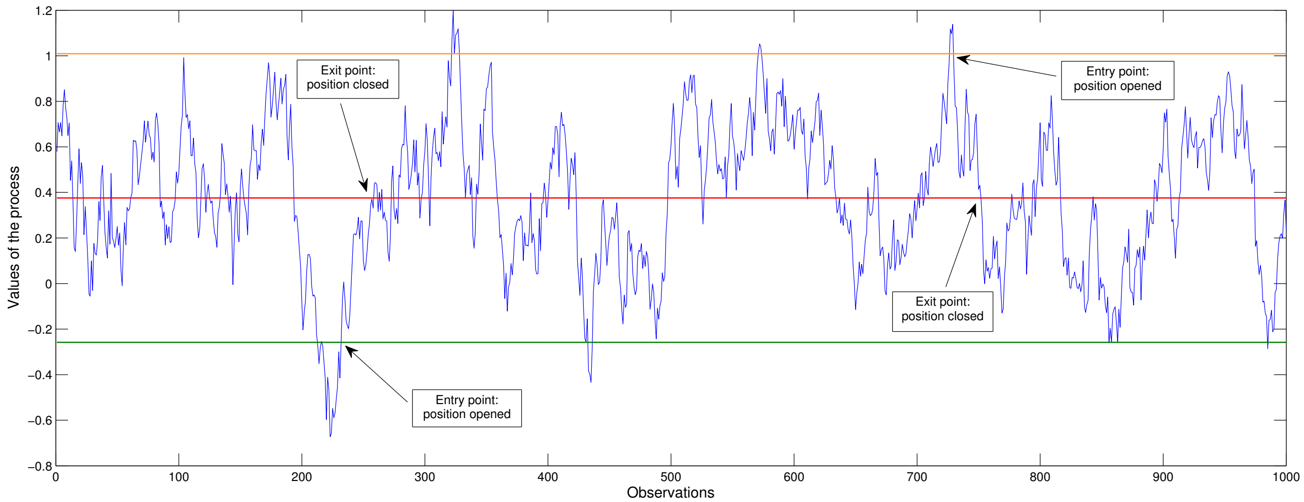
Table 4.16: Panel Probit regression of strategy excess returns on all the regressors explained in Section 2. The dependent variable takes value 1 if the strategy returns are strictly positive or 0 if the strategy returns are lower or equal to zero. Standard errors are robust. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Coeff | t-Stat | |
|---|---|---|---|
| Illiquidity | 3.586 | 2.94 | (***) |
| Dummy | 0.040 | 0.73 | |
| Interaction | -3.182 | -2.30 | (**) |
| Asset vola | -2.929 | -0.19 | |
| Strategy vola | 20.017 | 9.92 | (***) |
| Value | 0.000 | -0.61 | |
| Volume | 0.000 | -2.86 | (***) |
| Co-movement | 1.598 | 0.46 | |
| Constant | -1.515 | -33.37 | (***) |

Table 4.17: Multinomial Logit regression of strategy returns on all the variables described in Section 2. The dependent variable can take three values: 0 if strategy returns are 0, 1 if strategy returns are strictly positive and 2 if strategy returns are strictly negative. The basis for the multinomial regression is chosen to be 0, *i.e.* the cases when the strategy cannot open. Accordingly, below we report the results for the cases of positive and negative returns, *i.e.* when the dependent variable takes values 1 and 2 respectively. Standard errors are robust. For the interpretation of all the results, please refer to Section 4. The symbols (*), (**) and (***) refer to the significance at the 10%, 5% and 1% level respectively.

| | Positive returns | | | Negative returns | | |
|---|---|---|---|---|---|---|
| | Coeff | t-Stat | | Coeff | t-Stat | |
| Illiquidity | 6.640 | 2.74 | (***) | 8.686 | 2.82 | (***) |
| Dummy | 0.063 | 0.84 | | -0.085 | -0.78 | |
| Interaction | -5.830 | -2.20 | (**) | -6.543 | -1.88 | (*) |
| Asset vola | -22.465 | -0.99 | | -127.815 | -2.74 | (***) |
| Strategy vola | 41.680 | 15.19 | (***) | 47.919 | 14.29 | (***) |
| Value | 0.000 | -0.45 | | 0.000 | 2.81 | (***) |
| Volume | 0.000 | -3.09 | (***) | 0.000 | -2.21 | (**) |
| Co-movement | 4.502 | 0.65 | | 10.056 | 1.58 | |
| Constant | -2.609 | -37.66 | (***) | -3.484 | -37.75 | (***) |

Figure 4.1: Entry and exit points for the strategy. To shed light on how the strategy works, this figure displays the dynamics of 1,000 observations simulated from an Ornstein-Uhlenbeck process. A position is opened when the process crosses the upper (lower) boundary *from above (below)*. It is then closed either when it reverts back to the mean of the corridor and hits the latter, or as soon as it crosses once again the upper (lower) threshold stepping out of the corridor. A profit is ensured in case the process reverts to the mean of the corridor, as in the two cases illustrated here.



# Conclusions

In this thesis I have investigated several issues related to the behavior of the financial markets. I have started by underscoring the relevance of economic policy and institutional effectiveness as explanatory variables of the dynamics of the stock, CDS and forex markets. The key message of the first chapters was the low correlation between policy and politics, which can be exploited to create investment portfolios and which can also be beneficial to understand which countries are characterized by the best (worst) performances of the stock markets, the lowest (highest) default probabilities, and the lowest (highest) depreciation rate with respect to the US dollar.

In the second and third chapters I have dealt with the impact that extreme events have on the stock market. In Chapter 2 I have shown that the extreme correlation between return and trading volume during stock market crashes and booms turns out to be surprisingly low. This sheds light on the underlying causes of extreme price movements, which neither can they be identified in the overreaction of economic agents, nor in the irrationality of the latter. On the other hand, algorithmic trading, positive-feedback strategies and asymmetric information play a key role in determining market crashes.

After explaining the causes of the reactions of the stock market to extreme events, I have moved to propose a forecasting algorithm that turns out to be particularly useful to predict the future values of leptokurtic distributions where extreme events have a non-negligible impact. I have shown that an entropic cost function has higher predictive accuracy with respect to standard quadratic techniques.

I have concluded the thesis by investigating pairs trading, a famous statistical arbitrage investment strategy, showing that expected strategy returns incorporate an ex-ante compensation for expected illiquidity. Understanding the dynamics of the markets turns out to be very useful in that it allows an investor to develop and implement trading strategies able to generate consistently high returns.

Overall, the main goal of this thesis has been threefold. First, I am truly convinced of the importance of the channels linking politics and finance. Many avenues for further research in this area can and should be explored in the future, since these issues are becoming increasingly relevant in a world characterized, nowadays, by high political uncertainty. I therefore highlight these topics as very relevant for the whole society and for the academic community. Given the results shown in this thesis, I aim to increase the interest of academics in these political issues and their impact on the world of finance. Further research in this area is not only interesting academically speaking, but also of high relevance for the entire society.

Second, I wanted to shed light on the market dynamics in presence of extreme events, which have played a crucial role in history and in particular in the recent financial crisis. I aimed to suggest new ways to understand and deal with these extreme events, focusing on providing a forecasting method that outperforms standard quadratic techniques in presence of leptokurtic distributions where the impact of extreme events is remarkable. Last but not least, I have shown that understanding the dynamics of the markets can be beneficial, since it becomes possible to design trading strategies able to beat the market. Hence, thanks to all the aforementioned results, and focusing in particular on the crucial political phase that we are going through nowadays, I think that my thesis and its intellectual contribution can be useful and of interest for academics, practitioners, investors, but also for policymakers and the society as a whole.

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