

Louvain School of Management

Does the Economic Policy Uncertainty affect the Belgian stock market?

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Abstract

This master's thesis aims to study the impact of economic policy uncertainty, through the 3 versions of the EPU index for Belgium, namely the national, the French-speaking and the Dutch-speaking ones, on the Belgium stock market. In addition to the study of the predictive power of EPU indices on Belgium's national stock index (i.e., the BEL 20), we also studied whether this effect is size-dependent and sector dependent, as well as whether the predictive power is different during crisis periods. For all our analyses we worked with a lag of one month, using the excess stock returns of the month t with the EPU data of the month $t-1$.

Studying the predictive power of EPU indices on the BEL 20 between January 2000 and September 2022 we found a statistically significant impact. But contrary to our first hypothesis it was a positive impact, meaning that when the EPU level rose in month $t-1$, the excess stock returns in month t tended to rise. Concerning the size effect, we studied the predictive power of EPU indices on the BEL 20 and BEL Small excess returns between December 2002 and September 2022. Again, we found a positive impact on both stock indices, but contrary to our second hypothesis, the impact on large caps (i.e., the BEL 20) seems to be more important than on small caps (i.e., the BEL Small), as the beta coefficients linked to the BEL 20 are greater and more statistically significant than those linked to the BEL Small. For our third analysis, we regressed the excess returns of the Belgian sector indices on the EPU indices, between December 2008 and September 2022, to study whether the predictive power is sector dependent or not. We found that indeed, as we assumed in our third hypothesis, it is well sector dependent. Again, almost all the beta coefficients are positive, and the strongest impact is on the consumer discretionary and the industrials sectors. For our last analysis we wanted to study the predictive power of EPU indices during crises. To do so, we used two samples, one for the Subprime crisis between September 2008 and August 2010 and the second for the Covid crisis between March 2020 and August 2021. For our GFC sample we found that all the beta coefficients were positive but only one was statistically significant (between the BEL 20 and the French-speaking EPU). And for our Covid sample we found some positive and some negative links, but none were statistically significant. Moreover, in all our analyses we found no major and constantly better predictive power between the different versions of the EPU index for Belgium.

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List of abbreviations

BB: Beige Book

BLUE: Best Linear Unbiased Estimator

CBOE: Chicago Board Options Exchange

CPI: Consumer Price Index

EPU: Economic Policy Uncertainty

ER: Excess return

Fed: Federal Reserve System

FGLS: Feasible Generalized Least Squares

FOMC: Federal Open Market Committee

GDP: Gross Domestic Product

GFC: Global Financial Crisis

GICS: Global Industry Classification Standard

GLS: Generalized Least Squares

IMF: International Monetary Fund

NBB: National Bank of Belgium

OLS: Ordinary Least Squares

pp: Percentage point

REIT: Real Estate Investment Trust

R&D: Research and development

S&P: Standard & Poor's

VIX: Volatility Index

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Introduction

The goal of this master's thesis is to look at the impact of the economic policy uncertainty (EPU) on the Belgian stock market. We will focus on the Belgian stock market, because despite growing literature on the link between EPU and stock markets there has not been any study focusing on Belgium.

This master's thesis will be divided into two main parts: a theoretical one and an empirical one. In the theoretical part we will begin by defining some key notions such as uncertainty and what are the differences with the notions of risk. Then we will define the EPU index and explain how it is constructed, together with what are some of its advantages and some of its drawbacks. Later, we will explain some specificities about the EPU index for Belgium and what methodology the authors have used to compute it, as well as talk about the events that have impacted the EPU index in Belgium. After that we will talk about the link between uncertainty and the economy, covering both micro- and macro-level consequences of uncertainty. We will also discuss the link between uncertainty and recessions as well as recovery as it has been at the forefront of the uncertainty literature at least since the Subprime crisis.

In addition, we will cover some studies that have been realized about the link between the EPU index and the stock market of various countries. This is a topic of increasing importance in the uncertainty literature, and this will help us to formulate hypothesis for the empirical part.

In the empirical part, we will begin by looking at the impact of the three versions of the EPU index that exist for Belgium on the Brussels stock exchange, using the Belgian flagship index, namely the BEL 20. Most studies focus on that general link, but we will differentiate ourselves by conducting three more analyses. The first one will aim to look if there is a size effect in the predictive power of the EPU index on stock returns, by comparing the effect on the BEL 20 (composed of the 20 biggest and more liquid stocks trading on Euronext Brussels) to the one on the BEL Small (composed only of small caps only). The second one will aim to look at whether this predictive power is sector dependent or not. To do so, we will compare the predictive ability of the EPU indices for Belgium on the excess return of the different Belgian sector-based indices. Some studies have already made these special analyses for other countries, but they are still scarce. Our

third and last specific study will focus on the predictive power of EPU index in crises, more specifically during the 2007-08 financial crisis and during the Covid crisis.

For all our analyses and because this is a specificity of the EPU index for Belgium, we will look if there are some differences in the predictive power between the three versions of EPU index for Belgium (national one and Dutch- and French-speaking ones). Before conducting all these analyses, we will formulate hypothesis for each of them based on the literature. Then we will explain where we retrieve our data and what methodology we will use. And finally, we will detail the empirical results we obtain.

Theoretical part

1. What is uncertainty?

The Cambridge Business English Dictionary (n.d.) defines uncertainty as “the feeling of not being sure what will happen in the future”. Uncertainty is a key concept in human affairs and decisions making. Indeed, knowledge of the future is always imperfect and therefore, decisions are always made in presence of some uncertainty about their outcomes. We can thus consider that here the word uncertainty refers to the gap between what is known and what actually is or will be. So, uncertainty reflects an imperfect depiction of current conditions relevant to a choice, and the incomplete knowledge of the future consequences stemming from that choice (Encyclopedia.com, 2018).

More specifically, according to Bloom (2014), uncertainty is a broad and ambiguous concept that can include uncertainty over the path of macroeconomics items such as GDP growth, as well as over microeconomics phenomena like the growth rate of firms for example, but also noneconomic events such as war and climate change. It is multidimensional and a greatly nonlinear function of a variety of factors and researchers have focused on specific types of uncertainty (Rossi, 2020).

1.1. Difference between uncertainty and the notion of risk

Uncertainty and risk are intertwined concepts, but we can make distinctions between the two. In the common language, the word “risk” is usually used in a loose way to refer to any sort of uncertainty viewed from the standpoint of the unfavorable contingency i.e., it bears a negative connotation. While the term “uncertainty” is similarly used but with reference to a favorable outcome. For instance, we speak of the risk of a loss and the uncertainty of a gain. To get rid of the ambiguity between these 2 notions, Knight (1921) proposes a clear distinction, that has since been commonly used in economics. Knight defines risk as a quantity that can be measured and can thus be considered as a “measurable uncertainty” while true uncertainty is per se unmeasurable. Uncertainty is people’s inability to forecast the probability of events happening. It happens in situations that cannot be analyzed either on an ex-ante ground – because they are too irregular – or via empirical observation – because they are too unique.

Hence, the difference with risk is that when we are dealing with risk, we feel we understand what is going on and have some confidence in our assessment of the probability of occurrence of the different states. Because we can assign probabilities to the different events while facing risk, we can hope to produce a numerically balanced judgement. On the contrary, in a situation of uncertainty we do not have enough information to form probabilities about the different possibilities (De Winne, n.d.). And since uncertainty is not measurable it cannot be quantified and dealt through insurance or any other coverage (Rose, 2001).

1.2. Uncertainty in economic theory

Ricardo, one of the founding fathers of nineteenth-century classical economics, assumed a world of perfect certainty, where the path of the economy was determined by timeless natural laws of which economic decision-makers had complete knowledge (Davidson, 1999).

Similarly, in neoclassical theory, markets are seen as stable economic systems that converge toward an equilibrium position and that is free of uncertainty. The economic system and market can be described by laws. Economic agents are assumed to have all reliable information for decision making, and the future is known with certainty (Encyclopedia.com, 2018; Baltatescu, n.d.). According to Baltatescu (n.d.), the neoclassical approach excludes uncertainty from the analysis because the theoretical framework and the assumption that economic individuals have perfect rationality that goes with it, do not allow that theoretical approach to formalize uncertainty. Neoclassicals consider that when facing uncertainty i.e., without complete and perfect information, individuals cannot choose but irrationally.

On the contrary uncertainty is a central element of the Keynesian and post-Keynesian theoretical approach, it is its starting assumption. Because there is always some uncertainty, economic agents make expectations, based on subjective judgements, on which they decide investing or not. Keynesians and post-Keynesians also make the same distinction between uncertainty and risk as Knight (Baltatescu, n.d.). Keynesians consider that when in presence of risk, i.e., the probability of occurrence of the different events is known or can be estimated with confidence, the decision problem can be solved through a mathematical optimization process. But uncertainty is when the probability distribution

is not known so that, as Crotty (1993; as cited in Baltatescu, n.d.) says, the decisions cannot be modeled or subject for a process dominated by rationality. In this void of rationality Keynes considers that the feeling of trust and confidence in the public institutions, as well as the intuitions, the emotions and what he calls the “animal spirits” become predominant. Keynes’ “animal spirits” are all the non-rational and emotional factors that affect decision-making.

2. The Economic Policy Uncertainty

Although the impacts and the effects of policy uncertainty on the economy have been of interest for lawmakers, consumers, investors, economists, and researchers for more than 3 decades now, it has especially come back at the front of the preoccupations for economic agents after the global financial crisis (GFC) (Antonakakis, Chatziantoniou & Filis, 2013; Bloom, 2014).

Indeed, more and more economists and researchers were arguing that policy-related uncertainty played a key part in the slow recovery following the financial crisis from 2007-2008. For instance, in 2009 the Federal Open Market Committee (FOMC) and in 2012-2013 the International Monetary Fund (IMF) suggested that the uncertainty about US and European fiscal, regulatory and monetary policies played a part in the sharp economic decline in 2008-2009 and slow recoveries thereafter (Baker, Bloom & Davis, 2016). According to Baker, Bloom and Davis (2012b), the rationale was that when businesses and households are uncertain about future taxes, government spending levels, regulations, interest rates, etc., they are more inclined to delay consumption, investments, as well as slowing down hiring which hinders the recovering. This likely role of uncertainty in shaping the subprime crisis has focused policy attention on this topic. In addition, government economic policy is important because public investment and expenditures play a key role in the economy. For example, in 2009 in the US, federal, state, and local government expenditures amounted to \$5.9 trillion or 42.45% of the US gross domestic product (GDP) (Brogaard & Detzel, 2015).

Moreover, Bloom (2014) states that the greater availability of empirical proxies for uncertainty such as panel of firm-level outcomes, online news databases, and surveys is facilitating the empirical work thus boosting studies around it. Also, the rise of computing

power has made it feasible to include uncertainty shocks directly in a broad range of models, allowing researchers to abandon assumptions based on “certainty equivalence”.

And because in order to be able to study something you first need to quantify it, researchers have proposed different approaches to do so. But to identify something that is not directly measurable poses a significant challenge (Pastorek & Valovic, 2023). The Economic Policy Uncertainty (EPU) index developed by Baker, Bloom and Davis in 2012(b) is the most popular in the literature. The authors wanted their index to capture: a) the uncertainty about who will make economic policy decisions (e.g., who will win the next elections?); b) the uncertainty about what economic policy actions decision makers will undertake, and when; c) the uncertainty about the economic effects of policy measures (all past, present, and future measures); d) the economic uncertainty due to policy inaction and e) the economic uncertainty linked to national security concerns and other policy matters that are not chiefly economic in character (Baker, Bloom & Davis, 2013).

In this first version of the EPU index that was developed for the US, the index was built from three components. First, the frequency of mentions linked to economic uncertainty and policy in a set of 10 leading American newspapers¹. Second, the number of federal tax provisions set to expire in coming years. And third, the extent of disagreement among economic forecasters about the future federal government purchases and the future CPI level (Baker et al., 2012b). But the EPU indices for most of the countries available rely solely on one component, being newspapers coverage of some words that are identified as being linked to either uncertainty, economy, or policy. In 2016, Baker, Bloom and Davis published a new version of the EPU index for the US relying only on newspaper coverage.

2.1. How the Economic Policy Uncertainty (EPU) index is constructed

In their article of 2016, Baker, Bloom and Davis explain that for their modern version of the US EPU index it is only based on newspaper coverage. The index reflects the recurrence of articles in 10 large US newspapers² that include the following trio of terms: “economic” or “economy”; “uncertain” or “uncertainty”; and one or more of “Congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation”, or “White House” (including

¹ For the list see Appendix 1

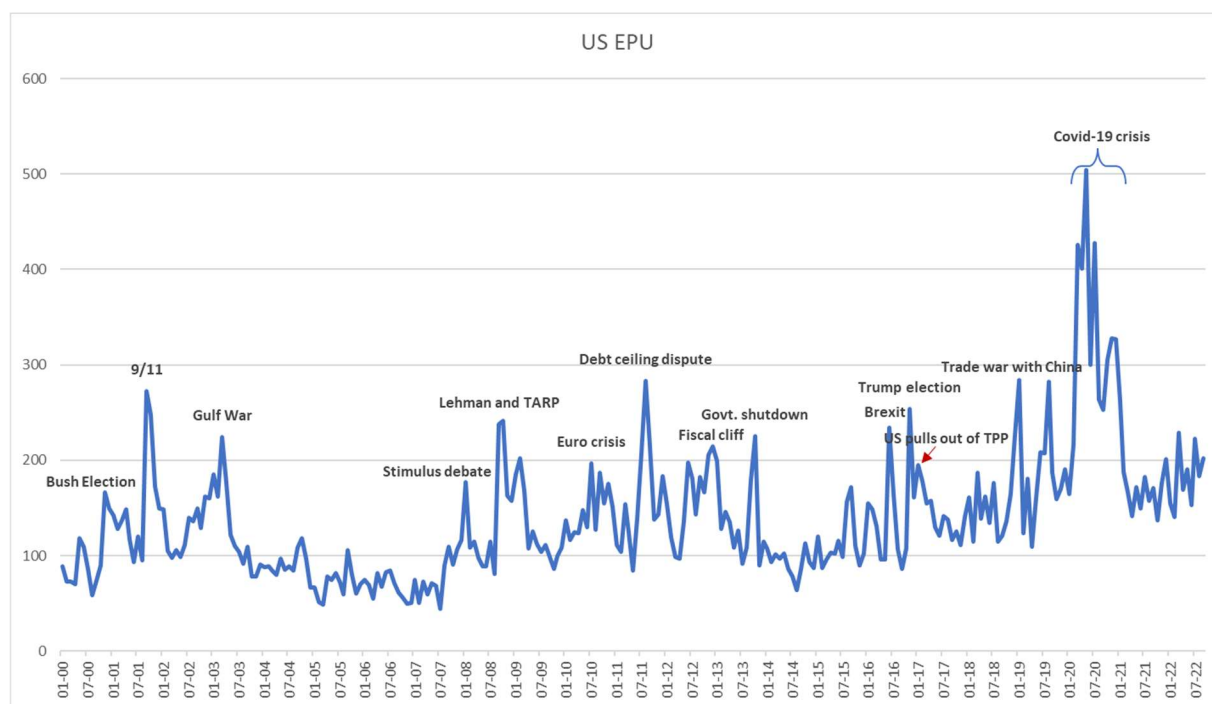
² For the list see Appendix 1

variants like “uncertainties”, “regulatory” or “the Fed”). Therefore, to meet their criteria an article must contain words in all the three categories relating to uncertainty, the economy, and policy.

According to Baker et al. (2016), an obvious trouble with these raw counts is that the overall volume of articles varies across time and newspapers. Therefore, the authors have scaled the raw counts by the total number of articles in the same newspaper and month.

If we look at the EPU index for the US during the 2000-2022 period, on the graph below, we see that it is both influenced by US-related events (such as Bush election or debt ceiling dispute) as well as more global events (such as the Euro crisis, the Brexit or the Covid-19 crisis during which it peaked). Baker et al. (2016) noted that it is the case for any given country that a wide range of domestic and international events influence the magnitude of policy uncertainty.

Graph 1: US news based EPU index from January 2000 to September 2022



Source: Data from www.policyuncertainty.com/us_monthly.html as explained in Baker, S. E., Bloom, N., & Davis, S. J. (2016). *Measuring Economic Policy Uncertainty*. *Quarterly Journal of Economics*, 131(4), 1593–1636.

2.2. Pros of the EPU index

Now that we have seen that the EPU index is a very popular index to quantify policy uncertainty, especially in its more frequent form as a news-based indicator only; and that we have explained how it is constructed, we are going to talk about some of its advantages and disadvantages as an index.

Firstly, the popularity of the index and its broad use in the literature can be explained by the fact that the EPU index is very intuitive and straightforward, easy to compute, and transparent, meaning there are no dubious details that could raise questions on the engineering behind the index (Pastorek & Valovic, 2023; Rossi, 2020).

Secondly, it is a model-free index thus the researchers have very few degrees of freedom, increasing the objectivity of the index. As Rossi has shown in its 2020 paper, the fact that it is a model-free index also makes it a better index to approximate nonlinear events such as the GFC for example. And uncertainty being by essence a nonlinear concept, it is understandable that it is better followed by news-based indices than by rigid approximations from a model.

Thirdly it is a real-time and immutable over time measure so that, it does not depend on any data vintage, which according to Rossi (2020), is a big advantage especially from a policymaker point of view.

And fourthly, the whole news-based EPU index relies on one assumption only, being that newspapers in the aggregate, talk proportionally and consistently more about uncertainty precisely when it is higher, and vice-versa.

Moreover, we have already seen that uncertainty is a broad and abstract concept that can be tied to a variety of factors. And this kind of concept is better represented and measured by news-based indices (Rossi, 2020). Indeed, surveys for instance are only available for a relatively restrained set of variables, and they need to be well identified (e.g., inflation or GDP growth). Another advantage of the EPU index is that as Rossi et al. (2019, as cited in Rossi, 2020) have said, it seems that it is more driven by ex-ante uncertainty, while other measures such as the model to approximate uncertainty developed by Jurado et al. in 2015 (as cited in Rossi, 2020) are more affected by ex-post uncertainty (i.e., uncertainty due to misspecification in the predictions). Newspapers can also be used for nowcasting – which is the prediction of the present, the very near future and the very recent past – as suggested by Thorsrud (2016 & 2018). The advantages of using news to nowcast is that

it is more similar to the information used by the economic agents to take their decisions and thereby shape the aggregate economic variations.

Indeed, contrary to the usual input for model-based nowcasting which usually comes from structured databases and professional data providers, the information in the newspapers is unstructured and does not come (directly) from professional data providers. Information from the newspapers can attain a broad population of economic agents and therefore also contribute to reduce informational frictions. Newspapers also have the advantage that they cover the broad economy which is not the case of most high-frequency data that usually focus on a specific financial metric.

Furthermore, Baker et al. (2016), have shown that their EPU index makes a good job to gauge the uncertainty via article counts. Indeed, they have shown that their index computed for the US has strong relationships with other measures related to economic uncertainty, such as the VIX and the mention of policy uncertainty in the Federal Reserve System's (Fed) Beige Books.

Concerning the VIX, the EPU index often moves in the same direction as Baker et al. (2016) find that there is a correlation of 0.58 between the VIX and the US EPU Index for the 1990-2016 period. But the two measures also show clear differences, especially in the amplitude of their movements³. For instance, the VIX responds more strongly to the 1997 Asian Financial Crisis, the Russian Crisis and subsequent LTCM default, the WorldCom fraud, and the Lehman Brothers bankruptcy, while the EPU index reacts more to the Gulf wars, the 9/11 and the debt ceiling dispute for example. These differences are not surprising and are due to the conceptual differences between these two indicators. Indeed, whilst the Chicago Board Options Exchange (CBOE) VIX reflects the implied 30 days volatility of the Standard & Poor's (S&P) 500 based on the options price; the EPU index stems to reflect broad policy uncertainty – thus not specifically related to the stock market – and with no explicit time horizon. The VIX also covers only listed firms, which according to Davis et al. (2007; as cited in Baker et al., 2016) only accounts for roughly a third of private employment, its scope is thus slimmer. Baker et al. (2016), have also compared the VIX to a newspaper-based equity uncertainty index⁴ they made and then obtained a stronger correlation of 0.73. This strong correlation validates the approach of frequency counts of newspaper articles to build a proxy of an important type of economic

³ See graph in Appendix 2

⁴ To do so, they replaced the P terms in the original EPU index by “stock price”, “equity price”, or “stock market”

uncertainty, it is therefore a proof of concept for the methodology underlying the EPU index. It also confirms that the differences in the topical scope between the EPU and the VIX are an important source of the dissimilarities of the movements of the two indices.

Baker et al. (2016), have also counted the frequency of the word “uncertain*” in the Beige Book to build another policy uncertainty indicator. The Beige Book (BB) is released eight times a year, before each FOMC meeting, and summarizes the views and preoccupations expressed by economists, market experts and other professionals to the twelve regional Federal Reserve Banks. The quarterly time-series correlation between the EPU index and the policy uncertainty indicator based on the BB is 0.54. Concerns about financial regulation and sovereign debt appear more noticeably in the BBs than in newspapers, while contrary to the press (but not surprisingly) the BBs almost never mention monetary policy uncertainty.

Karnizova and Li (2014) have also shown that the US EPU index based on newspaper only is a strong predictor to forecast future US recessions at longer horizons (six to nine quarters ahead in the quarterly sample). This index also enhances the predictive power of financial variables such as the term spread (i.e., the difference between the 10-year and the 3-month US Treasury yields) and the corporate spread (i.e., the yield on a AAA corporate bond relative to the yield on a 10-year Treasury). This potential use of the EPU index to forecast recession advocates for its publishing on a continuous basis.

Another important advantage to advocate for the use of the EPU index is that many countries, such as Belgium, which will be the country of interest for this paper, do not have “second moment” measure (such as the VIX for the US) thus, the news-based indices serve as welcome substitutes for those countries (Rossi, 2020).

2.3. Cons of the EPU index

After having explored some of the main benefits of the EPU index, let’s now delve into some of its drawbacks.

An important issue with the EPU index is that it tends to be quite noisy and volatile which makes the high frequency movements (that are often those of interest to policymakers) not very reliable. Indeed, as Rossi (2020) puts it up it is difficult to justify that uncertainty

moves up and down sharply several times in a few months, as is the case when looking at the US time series for example. Thus, when assessing uncertainty, it is important to evaluate the current level with a historical perspective by looking at the whole time profile. The high volatility and noisiness are one of the reasons we rather look at monthly data than daily ones, as daily data amplify this problem. Another trouble that makes it difficult to have relevant daily series is to have access to a big enough stack of news articles to be able to proxy underlying uncertainty with news counts on a day-to-day basis in a good enough manner. Rossi (2020) also points out that the noisiness issue gets worse when the media coverage and the country under consideration are smaller or less central than the US and the time-series then have a notably lower signal-to-noise ratio. This is something we will have to keep in mind while looking at the EPU series for Belgium.

Another problem with the EPU index is that we cannot ensure that the index responds only to domestic factors. Indeed, as explained by Hatzius, Phillips, Stehn and Wu (2012), it is likely that a big part of the increase in the EPU index for the US around 2011-2012 was due to the European crisis despite not really affecting the policy uncertainty of the US. For instance, the Euro debt crisis is likely to be treated in a similar manner in both the *Financial Times* (a UK newspaper not used in the construction of the EPU index for the US) and the *Wall Street Journal* (a source for the US EPU index).

Konczal (2012; as cited in Peric & Soric, 2017) which was one of the first important authors to critic the EPU index as he disapproved its methodological construction as well as its interpretation; stated that its main weakness was that it is an upward biased index. Because each mention of “economic uncertainty” (even in a positive meaning such as uncertainty reduction) is perceived as a rise in the actual uncertainty as accounted by the index. Moreover, this is amplified by the strong negative bias of the media, as has been documented in numerous studies (e.g., Hester & Gibson, 2003 as cited in Peric & Soric, 2017). Additionally, Pastorek and Valovic, have found in their 2023 paper, that over longer time periods (such as 30 years), EPU indices show a clear upward trend that they do not see in alternative indices that proxy uncertainty, and this could be one of the reasons.

Pastorek and Valovic (2023), also point out that the articles used to make the index are usually obtained from newspaper databases where the obtained set of articles is greatly dependent on the selected keywords and query used (usually a set of keywords that the

article has to meet). But the selection of keyword is strongly subjective, and the search does not consider polymorphism or potential synonyms of the keywords used in the query. It means that only the articles that present an absolute match between the keyword in the query and in the article are taken into consideration for the index. This can cause some relevant articles not to be integrated in the index computation, despite containing semantically similar words. So, the method used for the EPU index can lead to false negatives. Additionally, as Krugman (2011) points out because the EPU index is based on word counts from newspapers it does not sort out articles that could be seen as propaganda pushed by the newspaper editors.

Furthermore, the methodology of Baker et al. (2016) does not allow to differentiate between articles that discuss a true in-depth uncertainty in the economy and articles that only mention it superficially. All the articles therefore have the same weight in the index. Also, it is possible that a random distribution of words in the article satisfies the condition. So, for example, an article that has many words has more chance to fulfil the condition as a single word from each category (E, P and U) may appear in different paragraphs and be used in different context. The probability of this false positive error increases with the number of words in the three categories (E, P and U). Concerning the number of keywords, there is thus a trade-off between rising the number to improve the identification of articles and decreasing the number to reduce the probability to have irrelevant articles considered in the index. To counter that, Pastorek and Valovic (2023), propose to weight each article individually. More specifically, it would mean that each selected articles (that has at least one word from each category) would be given a bigger weight if it contains more of the selected keywords. They find that using a weighting method can allow to obtain more stable index parameters whatever the number of included keywords in the search query is. It may also decrease the error rate of the original methodology of Baker et al. (2016). Because if there is a false positive (an article that is wrongfully selected due to random distribution of words in the text that causes random fulfilment of the condition of word combination despite not directly being related to economic-policy uncertainty) it should receive less weight as the trigger words potentially appear not often in the article.

Besides, in the composition of the index, the articles that are retained because they meet the conditions for EPU keywords are divided by the total of articles published in any given month, forming this ratio:

$$\frac{EPU \text{ relevant articles in newspaper } x \text{ in month } y}{\text{Total number of articles in newspaper } x \text{ in month } y}$$

But the caveat with this ratio is that it does not control for the composition change in newspaper over time, which naturally evolves. For instance, moving from a high quantity of articles to longer articles that consider the topic more deeply or changes in the overall number of articles published in a specific category. These transitions will impact the denominator of the ratio. Nevertheless, in this case the ratio change over time may reflect changes in the journal or the choice of individual editors rather than long-term trend in the index. On that account, when using data regarding economic-political uncertainty, interrogation emerge to know if the levels of uncertainty over time are due to an actual increase in uncertainty or these transitions (Pastorek & Valovic, 2023).

3. The EPU index for Belgium

Algaba, Borms, Boudt and Van Pelt (2020) developed an EPU index for Belgium. The particularity for Belgium is that it is a country with three official languages with French and Dutch being the main ones (German is excluded because the German-speaking community counts less than 80 000 inhabitants, and only one newspaper, the “Grenz-Echo”). Therefore, it allows the authors to develop two regional versions of the EPU index, i.e., an index for Flanders based on Dutch-speaking newspapers and an index for Wallonia based on French-speaking newspapers. Then, to make the countrywide Belgium index the authors merge the two regional ones.

3.1. The construction of the Belgian EPU index

To construct their indexes, Algaba et al. (2020) use the same methodology as described in Baker et al. (2016), that constructed a monthly news-related EPU index for the US. The different steps are:

First, to select the newspapers of interest. Here the authors have selected the following eight Flemish newspapers and five newspapers in French, that you can see in table 1 below.

Table 1: List of newspapers used for the Belgian EPU, sorted by language

Dutch-speaking newspapers	French-speaking newspapers
De Tijd	L'Avenir
De Standaard	La Dernière Heure
De Morgen	La Libre Belgique
Het Laatste Nieuws	Le Soir
Het Nieuwsblad	L'Echo
Gazet van Antwerpen	
Het Belang van Limburg	
Het Volk*	

* The newspaper “Het Volk” is included despite seizing activities in 2008 as it is an historically important news source.

Source: Algaba, A., Borms, S., Boudt, K., & Van Pelt, J. (2020). *The Economic Policy Uncertainty Index for Flanders, Wallonia and Belgium*. BFW Digitaal / RBF Numérique, 2020/6.

The authors have retrieved the articles from Belga – the Belgian news agency – which archive contains over 40 million media news articles in both Dutch and French. They have cleaned the data by eliminating exact duplicate articles as well as articles that are irrelevant to economic policy uncertainty (such as sport or art news). Nonetheless, near-duplicate entries are kept, because they are often the same publications but by different newspapers. Algaba et al. (2020), have also decided to filter out too short (less than 450 characters) and too long (more than 7500 characters) articles, as these are more sensitive to a biased measurement of EPU relevance. They have also made the choice to exclude online newspaper content. Firstly, to have more comparability of the data universe across time, since online publications have gained importance compared to the beginning of the period covered. And secondly, because online publications can be different when it comes to the level of uncertainty expressed as they typically serve other purposes, such as monetization.

Second, to count the number of articles containing at least one economic (E) keyword (such as unemployment, consumption, GDP, etc.), one policy (P) keyword (e.g., ECB, budget, government, etc.), and one uncertainty (U) keyword (for example, alarming, fluctuations, worrying, etc.); in the native language of the newspaper in question. These are thus the raw number of EPU articles that are considered. The E and P categories are required to filter the news to the right topic, here economic policy. And the U category can

be seen as a “sentiment” driver. The authors start from the list of Dutch words used by Kroese et al. (as cited in Algaba et al., 2020), who based themselves on the seminal paper of Baker et al. (2016). The words that are specific to the Netherlands are eliminated and the keywords are limited to single words. The Flemish word list⁵ is then translated in French⁶.

Third, to scale the raw EPU count by a measure of the total number of articles in the same newspaper and month. This is, as explained above, to eliminate the trouble linked to the fact that the overall volume of articles varies across time and newspapers, as suggested by Baker et al., (2016).

And fourth, Albaga et al. (2020), normalize the newspaper-level series to unit standard deviation for a reference period up to 2011 (i.e., they divide each index by its standard deviation). And as a final normalization, they bring the mean of the averaged series before 2011 to a level of 100 (meaning they divide the index by its mean and multiply by 100). Finally, the countrywide Belgium EPU index is simply an average of the resulting Dutch-speaking and French-speaking EPU indices.

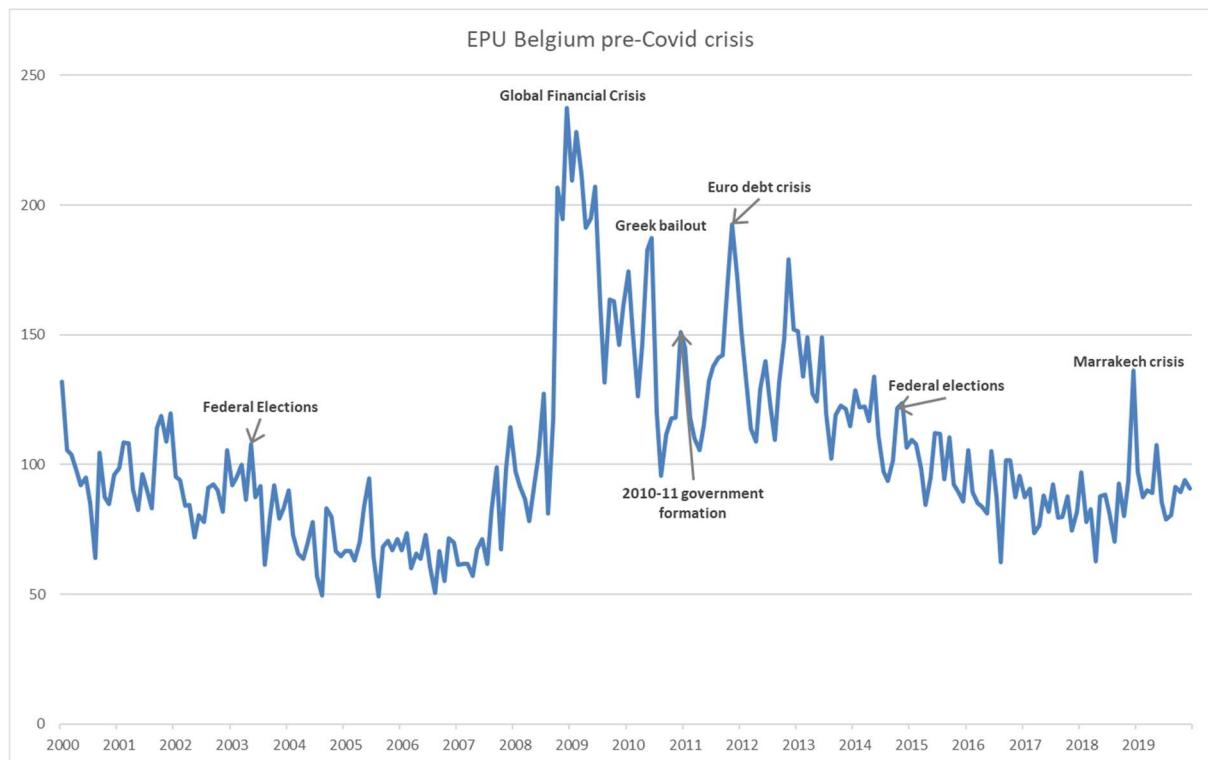
3.2. Belgian EPU time-series and events

At the time where we are writing these lines, the available monthly data for the Belgian EPU index on https://www.policyuncertainty.com/belgium_monthly.html range from January 2000 to September 2022.

If we look at the data from January 2000 to December 2019, to exclude the Covid effect we obtain the following graph:

⁵ See Appendix 3 for the full Flemish word list

⁶ See Appendix 4 for the full French word list

Graph 2: Belgian EPU index from January 2000 to December 2019

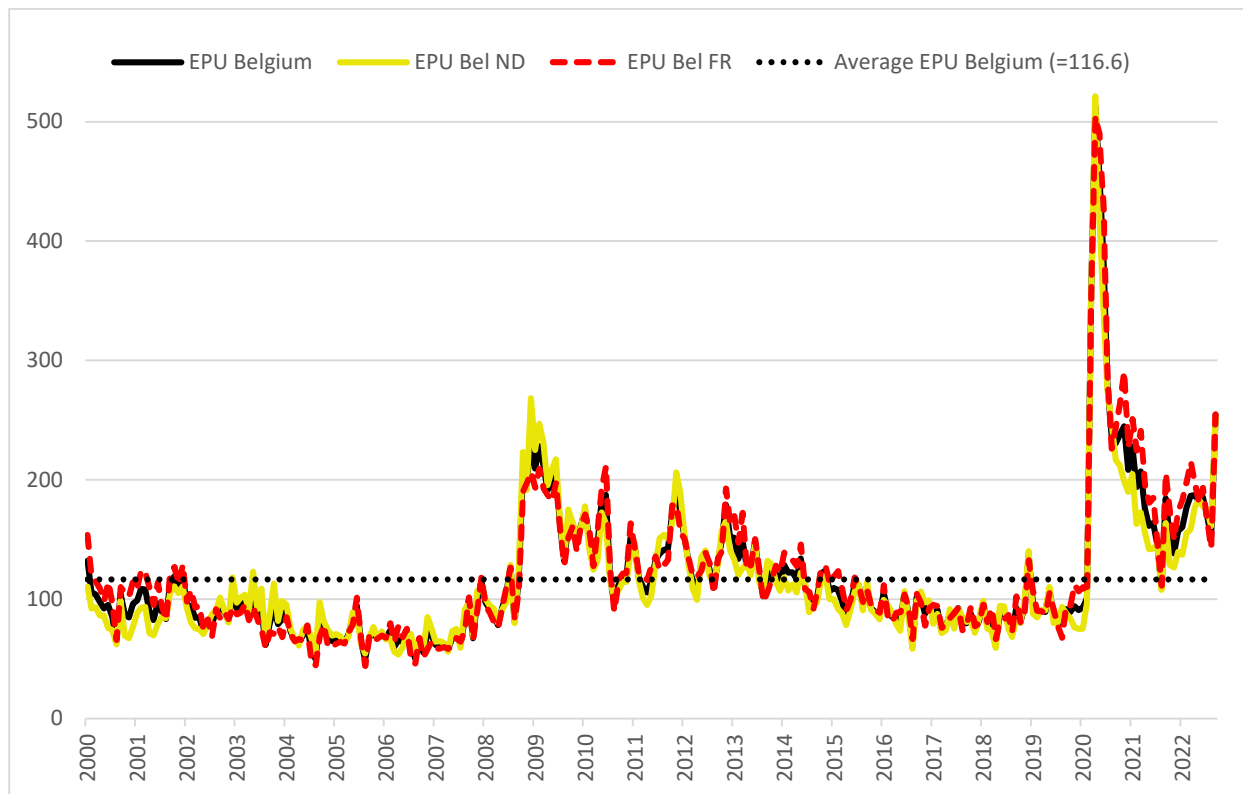
Source: Data from www.policyuncertainty.com/belgium_monthly.html as explained in Algaba, A., Borms, S., Boudt, K., & Van Pelt, J. (2020). *The Economic Policy Uncertainty Index for Flanders, Wallonia and Belgium*. BFW Digitaal / RBF Numérique, 2020/6.

When looking at this graph we see that the Belgian EPU index is quite volatile and that spikes in it are associated with Belgian political events such as the political crisis of 2010-2011 around the government formation and the governmental crisis tied to the Marrakech pact. But it is also impacted by more global economic events such as the Subprime crisis and the Euro debt crisis.

Looking at the Belgium EPU for the whole period (i.e., from January 2000 to September 2022) in graph 3, we see a sharp peak during the Covid crisis with a maximum value of 512.86 in April 2020. We can also note that from March 2020 to September 2022 the index values have almost always been above the average of the full period of 116.6, denoting high policy uncertainty. And if we look at the EPU index based on French-speaking newspapers and the one based on Dutch-speaking newspapers we see that there are some differences, despite strongly matching with a correlation of 0.94⁷. We can also see on the graph 3 below that the GFC was more covered in the Dutch-speaking press while the Covid crisis was more covered in the French-speaking press, except for the very peak.

⁷ For the correlation table see Appendix 5

Graph 3: Belgian, Dutch-speaking and French-speaking EPU indices from January 2000 to September 2022



Source: Data from www.policyuncertainty.com/belgium_monthly.html as explained in Algaba, A., Borms, S., Boudt, K., & Van Pelt, J. (2020). *The Economic Policy Uncertainty Index for Flanders, Wallonia and Belgium*. BFW Digitaal / RBF Numérique, 2020/6.

4. Uncertainty and the economy

Uncertainty, whatever the way you decide to proxy it, is clearly countercyclical, meaning that it rises when the economy goes down, and decreases when the economy is growing⁸. And the EPU index is no exception to that as it is on average 51% higher during recessionary periods. Moreover, the kind of exogenous shocks that can lead to recessions – such as wars, oil price jumps, and financial panics – typically also raise uncertainty (Bloom, 2014). Indeed, these kinds of bad events distort people's confidence in their estimation of economic growth, hence increasing macro and micro uncertainty. So, it is clear that uncertainty and recessions are correlated but to know which causes which is a different kettle of fish.

⁸ As is visible on the graph in Appendix 6

4.1. Micro-level consequences of uncertainty

A key concept in the economic literature concerning uncertainty is the concept of option value, sometimes also referred to as real option. This concept is often used to argue that uncertainty impact the behaviour of economic agents in a way that is often detrimental to the economy. The option value is the value of having the possibility to postpone an investment decision when facing uncertainty, and instead wait and collect more information before committing to an irreversible investment. In his analysis about the flow of information and option value, Bernanke (1983) bases himself on two assumptions that can be considered as necessary conditions to have a value option. These are: a) that the individual investment projects are economically irreversible meaning that once undergone these projects cannot be “undone” or transformed into a completely different type of project without incurring prohibitive costs. And b) that relevant new information to evaluate the long-term project returns arrives over time, in order that the potential investor can improve his chances of taking a good decision by waiting. For real option effects to be present, the company must also have the ability to wait and delay the investment (Bloom, 2014). Therefore, if firms are racing, for instance to be the first to patent an innovative technology or launch a new product on the market; or if postponing would be extremely costly, the option value vanishes.

Bloom (2014) gives the example of a supermarket chain that owns an empty parcel of land on which it has the option to build a new store. If the supermarket is uncertain about the future – e.g., because it is uncertain about whether a local housing development will go through – it may choose to wait before deciding to build the supermarket. If the housing development takes place, the supermarket can build the site, if not it can wait and defer the decision, thus avoiding a costly mistake. The option value increases with uncertainty and this concept can thus explain why in high uncertainty period, firms are more cautious about actions which have high reversing costs, such as hiring and investing. Further, Baker et al. (2016), have found that higher policy-uncertainty has a bigger negative impact on investment and employment for firms that belong to policy-sensitive sectors, such as defense, health care, finance, and infrastructure construction. This stronger impact of policy-uncertainty can be explained by the fact that sectors such as defense and infrastructure construction rely greatly on public spending and sectors such as healthcare and finance are strongly exposed to major shifts in regulatory policy. This result implies

that not all sectors react the same way to uncertainty and advocate for a sector analysis that we will undergo in the empirical part of this paper.

We have seen that higher uncertainty can have detrimental effects on investment and hiring through real option effects. But perhaps more surprisingly, uncertainty can also potentially have some positive effects at the firm-level, later positively impacting long-term growth. One channel through which uncertainty can positively impact investment at the firm-level, is the growth option concept (Bloom, 2014). This concept states that uncertainty can foster investment if it raises the size of the potential prize. Growth options are often cited as a justification to the internet boom and bubble of the late 1990's, that later busted and led to the dot-com crisis of the early 2000's. Companies were unsure about internet, but that uncertainty stimulated their investments. The worst outcome for a firm developing new websites was losing their developments costs, but the best outcome looked ever more profitable as the uncertainty around internet grew. As developing websites took time and resources, making one was seen as buying a "call option" on the future success of internet. In addition, Kraft, Schwartz, and Weiss (2013; as cited in Bloom, 2014), have demonstrated how growth options are especially important for research and development (R&D) intensive firms, to the point that stronger uncertainty can increase their stock value. This also points out to uncertainty having different effects on firms depending on their sector.

The real option concept can also be used to justify that uncertainty hampers private consumption especially of durable goods, such as housing, cars, and furniture (Bloom, 2014). Indeed, if an individual is uncertain about its future income, he might decide to wait before buying a new car for example. So, the higher the uncertainty about the real income, the higher is the option value to delay consumption of durables. Moreover, in period of strong uncertainty, consumers will increase their precautionary savings consequently further reducing their consumption. Hence, with the real option concept as a rationale it is commonly accepted in the literature that higher uncertainty hurts long-lived investments, hiring, and private consumption which will stall economic growth (e.g., see Bernanke, 1983; Baker, Bloom & Davis, 2012a; Makin, 2012; Bloom, 2014).

Stronger uncertainty will also increase the costs of financing, because in period of heightened uncertainty investors will require higher risk premia (Bloom, 2014) and because most of uncertainty is macroeconomic by nature and therefore difficult to

diversify (Baker et al., 2012a). In addition, Bloom (2014) notes that uncertainty also increases the default probability, which push the default premium up and augment the deadweight cost of bankruptcy. The higher financing costs can further reduce investment and impede micro and macro growth.

4.2. Macro-level consequences of uncertainty

The reductions of investment, hiring, private consumption, productivity growth, etc. typically induced by higher uncertainty that happen at the micro level (i.e., at the firm level or at the individual economic agent level) then aggregate and slow economic growth at the macro level. Indeed, Baker et al. (2016) have shown that policy-uncertainty foreshows reductions in investment, output, and employment in the US. And this has been empirically tested for other countries than the US. For example, Bhagat, Ghosh and Rangan (2016), have found that the Indian GDP and Indian fixed investment are negatively correlated to the Indian EPU index, and that the economic magnitudes of these relations are quite significant. And Ghirelli, Gil, Pérez and Urtasun (2019), conducting a study about Spain, found that GDP, private consumption, capital goods investment, and hours worked, all reacted negatively and significantly to unanticipated shocks in both financial and economic policy uncertainty. Additionally, they also noted that GDP and private consumption reduction were more persistent (lasting between 4 and 7 quarters after the shock) than investment, which initially reacts with a larger amplitude, but then the effect fades away more swiftly, three quarters after the shocks.

4.3. Uncertainty and recessions

As explained above, uncertainty and recessions are strongly correlated but the sense of the causation is less clear. As we have seen, uncertainty often damages the economy and so it could potentially cause recessions.

However, recessions could also increase uncertainty via four channels. Firstly, when business is good, firms engage in active trading, which aid to generate and spread information (Van Nieuwerburgh and Veldkamp 2006; Fajgelbaum, Schaal, and Tashereau-Dumouchel 2013; as cited in Bloom, 2014). But when business is bad, activity declines, reducing the flow of new information and thus increasing uncertainty. Secondly, when the economy is growing and it is “business as usual”, individuals are more confident

with predicting the future. But recessionary episodes happen scarcely, so that economic agents are still unfamiliar with them, and have trouble predicting the time ahead. Thirdly, unclear and/or hyperactive public policy might rise uncertainty. When the economy is doing well, politicians prefer status quo in a “if it is not broke don’t fix it” spirit (Pastor and Veronesi, 2011; as cited in Bloom, 2014). But when the economy turns down, politicians are enticed to experiment, increasing policy uncertainty. Consistent with that the EPU rises during recessions, as is particularly blatant during the GFC (Baker et al., 2012b). Fourthly, when business is sluggish, it is cheap to experiment new ideas and to divert unused resources to R&D (Bachman & Moscarini, 2011; D’Erasmus & Moscoso-Boedo, 2011; as cited in Bloom, 2014). This dynamic causes increased micro-uncertainty possibly feeding into higher macro-uncertainty. Therefore, it seems that uncertainty and recessions both reinforce themselves forming a vicious circle.

Thus, we know that uncertainty and recessions happen together, and both seem to reinforce themselves forming a vicious circle. But one of the main challenges of the uncertainty literature is to differentiate the impact of uncertainty from the impact of recessions. As stated by Bloom (2014, p.167): “We know that uncertainty moves with the business cycle, which raises the question of how to distinguish the separate causal effects of higher uncertainty”.

In addition, Bloom (2009) also argues that because second-moment (i.e., temporary uncertainty) shocks give rise to large plunge in output, employment, and productivity growth⁹, it lays out an alternative mechanism to first-moment (productivity and/or demand) shocks for generating recessions. Thus, recessions could simply be the consequences of higher uncertainty.

4.4. Uncertainty and recovery

A debate that is at the forefront of the uncertainty literature is about whether uncertainty harms and slows recovery downs or not, and this was specifically discussed about the recovery from the subprime crisis.

⁹ See Appendix 7 for the graph of the impact of an uncertainty shock on aggregate output

As we have explained, recessions and uncertainty are linked, and it seems that uncertainty can even lead to recession. Policymakers seem to think that uncertainty has played a prime role in the GFC and the slow recovery thereafter. For example, in 2012, Christine Lagarde, then Managing Director of the IMF, said: “There is a level of uncertainty which is hampering decision makers from investing and from creating jobs” (IMF, 2012; as cited in Bloom, 2014, p.171).

As we have seen, uncertainty can damage the economy and possibly be one of the factors leading to recessions. Several papers (e.g., Baker et al., 2012a; Makin, 2012) have argued that because uncertainty is damaging the economy (for example, through real option effects and higher cost of financing), when it is persistent it is harming and slowing the recovery. Moreover, financial crises create strong policy uncertainty, because the outcome linked to potential policy-paths cannot be estimated, and economic institutions are often unequipped to deal with that uncertainty, having to take decisions while being in the fog. As said by Knight (1921; as cited in Makin, 2012, p.3): “The use of resources in reducing uncertainty is an operation attended with the greatest uncertainty of all”. The outbreak of a financial crisis forces policymakers to quickly react and lead to policies that are often far from ideal (Makin, 2012). And Makin (2012) argues that since 2010, too many policy measures have contributed to sustain the recession.

But to researchers arguing that the lasting uncertainty stemming from the 2007-2008 crisis has led to weaker hiring and investment, Mishel (2011) retorts that investment actually rose more in the GFC recovery than in the preceding two recoveries, and about the same as the 1980s recovery¹⁰. Also, the recovery from the GFC followed the typical path (or was even slightly better) of recovery from crisis following a credit boom and bust¹¹, advocating that uncertainty is not needed to explain the slow recovery from the great recession (Schularick & Taylor, 2012; as cited in Hatzius et al., 2012). Moreover, in small businesses survey, the respondents pointed “poor sales” as their biggest preoccupation under Obama’s presidential term, during the aftermath of the GFC, in front of “taxes” and “regulations”¹². It therefore suggests that it was low demand that was holding back the economy rather than fear of regulation and uncertainty. In addition,

¹⁰ As is visible on the graph in Appendix 8

¹¹ See graph in Appendix 9

¹² As is visible on the graph in Appendix 10

Hatzius et al. (2012) argue that most of the increase in policy uncertainty was probably a result of economic weakness rather than its cause.

So, although high levels of policy uncertainty seem to be associated with weaker growth prospects, and uncertainty is strongly correlated with recession; it is difficult to establish that it is specifically political uncertainty that causes these gloomy economic developments, as many factors move at the same time in the economy (Baker et al., 2012a). And the econometric evidence about that cannot be considered anything more than suggestive (Bloom, 2014).

5. Uncertainty and the stock market

We have seen that elevated uncertainty generally harms the economy, sometimes even possibly leading to recessions. We will now look at the impact of heightened uncertainty on the stock market.

Political uncertainty seems to have two conflicting effects on stock prices. Firstly, policymakers often step in during troubled times, which might lead investors to think that they provide put protection on asset prices. In addition, policy changes usually occur after period of unusually low realized profitability (or downturn), so they will typically rise firms' expected profitability. Pastor and Veronesi (2012, 2013) call this the cash flow effect and it is expected to increase stock prices. Secondly, discount rate is increased by policy changes because the new policy's consequences on profitability are uncertain and political uncertainty is not completely diversifiable; and non-diversifiable risk tend to increase the discount rate. This discount rate effect is expected to drive stock prices down. Pastor and Veronesi (2012) find that the discount rate effect more than cancel the cash flow effect, except if the old policy's impact is recognized as sufficiently negative. Therefore, in most cases, political uncertainty will hurt stock prices. Moreover, when the returns following an announcement are positive, they are typically small as they generally happen in an economic context where they were expected, and so the effects were already priced in. But negative returns tend to be greater since they usually happen when the announce of a policy change carry more surprise. The expected announcement returns are also more negative when the policy uncertainty is larger.

Furthermore, political uncertainty leads to increase in risk premia because investors require compensation for uncertainty surrounding the outcome of political events. This

drives stock returns to be more volatile and more strongly correlated across firms. This political risk premium is also greater when the economy is in a bad state (Pastor & Veronesi, 2012, 2013).

Testing empirically the impact of US EPU on the US stock market from 1900 to 2014, Arouri, Estay, Rault and Roubaud (2016) find that a rise in the EPU level is associated with a fall in stock returns. To do so, they use a linear regression with the stock market return (R_{it}) as the dependent variable and the lagged return, a vector of uncertainty variables (UNCERT) and a vector of control variables (CONTROL) as independent variables, obtaining the following equation:

$$R_{it} = \alpha_{St} + \beta_{St} R_{i,t-1} + \phi_{St} \text{UNCERT} + \varphi_{St} \text{CONTROL} + \varepsilon_{it}$$

They also note that this effect is the strongest and more persistent during extreme volatility periods, which on their horizon correspond to these recessionary periods: September 1929 – October 1933 (the Great Depression), August 1937 – November 1938 (depression in the US) and September 2008 – April 2009 (the GFC). Negative effects of EPU on the stock market were also found for Canada for example (Batabyal & Killins, 2021). For their research the authors used a nonlinear autoregressive distributed lag model (NARDL) which allows them to investigate the asymmetric relationships between stock market and policy uncertainty. Testing the predictive power of EPU indices with a lag of one month on market excess returns for 16 countries (Australia, Brazil, Canada, China, France, Germany, India, Ireland, Italy, Japan, South Korea, the Netherlands, Russia, Spain, the UK and the US), Phan, Sharma and Tran (2018) have found statistically significant negative beta coefficient for 6 countries out of the 16 (Australia, Canada, Italy, Japan, South Korea, and the US).

According to Batabyal and Killins (2021) if uncertainty grows, the investors become more risk-averse and adjust their portfolio by decreasing its risk, to hedge against risky returns. They thus sell assets decreasing their prices. And when uncertainty diminishes the investors have a greater appetite for risk and bid-up the assets' prices. Brogaard and Detzel (2015), find a negative contemporaneous correlation between changes in EPU and market returns, and they argue that is due to increase in expected returns. But they also find modest evidence of a positive link between current levels of EPU and future market excess returns. Chiang (2022) also argues that investors who bought a stock during a

period of elevated uncertainty have a risk premium that should lead to excess returns. This suggests that EPU has real asset-pricing implications.

While studying the effect of EPU on Chinese stock markets, Chen, Jiang and Tong (2018), have shown that the predictive ability of the EPU is stronger for small caps which is consistent with the observation that small caps are often harder to value and more prone to speculation (Baker and Wurgler, 2006, 2007; as cited in Chen et al., 2018).

Furthermore, as we have seen, Baker et al. (2016) argue that policy uncertainty has not the same impact on every sector and that the impact is greater on more policy-sensitive sectors. Pastor and Veronesi (2012) have also found that the higher the exposure of a firm, the higher the expected returns. Having said that, it is important to note that the political risk premium is state dependent and can be negative. And Phan et al. (2018), have shown that EPU has relatively higher influence on some sectors than others and that stock return predictability is sector dependent. This argues for a sector analysis of the impact of EPU on stock market returns for the empirical part of this paper.

The classic predictive regression model with EPU as a predictor of stock returns can be described as

$$ER_t = \alpha + \beta EPU_{t-1} + \varepsilon_t$$

According to Phan et al. (2018) this model is easy to estimate but has several cons, because it potentially suffers from problems of persistency, endogeneity, and heteroskedasticity. Consequently, the OLS estimator of β is no longer unbiased. To counter these issues in the predictive regression, Phan et al. (2018) use the feasible generalized least squares (FGLS) estimator as recently developed by Narayan and Westerlund (2015; as cited in Phan et al., 2018). This allows to test the predictability while accounting for information from the heteroskedasticity of the predictor and the regression error.

Empirical part

In this empirical part, we will begin by explaining what analyses we will make and what results we are expecting, formulating hypothesis. Then we will explain with which data we will work and what methodology we will use. Finally, we will analyze and explain the results we obtain.

We will start by exploring the impact of the EPU index on the excess returns of the BEL 20¹³ and the BEL Small¹⁴. The BEL 20 is the flagship index of the Brussels stock market, it reflects the 20 stocks with the largest free float listed on Euronext Brussels. The BEL 20 thus represents the 20 largest and most actively traded stocks of Euronext Brussels. The BEL Small is composed of stocks that are not members of the BEL 20, have a free float market capitalization higher than the level of the BEL 20 multiplied by 5500 (for the entry level; the exit level is BEL 20 times 4500), and have a free float velocity of at least 15% (10% for current members)¹⁵. The goal of the BEL Small is to represent the small cap stocks of Euronext Brussels, while still being liquid enough to ensure that the index is investable. Both indices are free float market capitalization weighted. With this analysis we aim to see if the EPU index has an impact on the Belgian flagship stock index (i.e., the BEL 20) that can be used to proxy the Belgian stock market and if this effect is different compared to the one on the BEL Small. This analysis will therefore allow us to study whether policy uncertainty affects stocks differently given their size.

We will also make a sector analysis by comparing the effect of EPU on each sector-based index for Euronext Brussels¹⁶. These indices are full market capitalization weighted. With this analysis we will see if predictability with EPU index is sector dependent or not. Finally, we will also study whether the prediction power of the EPU index is higher during high uncertainty periods such as the GFC or the Covid crisis.

It is important to note that because one of the particularities of the EPU index for Belgium is that there exist sub-indices based on languages, we will also each time see if the

¹³ See Appendix 11 for the composition of the BEL 20

¹⁴ See Appendix 12 for the composition of the BEL Small

¹⁵ See Appendix 13 for the rulebook of the BEL 20 and the BEL Small

¹⁶ See Appendix 14 for the rulebook and Appendix 15 to 25 for the composition of each index

predictability varies based on which version of the index we use (either the national, the French-speaking or the Dutch-speaking one).

1. Hypothesis

1.1. Negative impact

We expect EPU to have a negative impact on the stock market, meaning that when the EPU value rise the returns should decrease. This should translate with a negative beta when we regress the stock market excess returns on the EPU index. As this is what has been found in the Phan et al (2018) article from which we replicate the methodology, as well as in Arouri et al. (2016) and Babsabab and Killins (2021) for example. The last two studies use no lag in their model, however.

1.2. Size differences

We expect the effect of EPU to be stronger for small caps stocks as demonstrated by Chen et al. (2018). This is intuitive as small caps are generally more volatile, less covered by analysts and considered to be riskier. Thus, we expect the beta linked to EPU to be more negative in the regression with the BEL Small as the independent variable compared to the one with the BEL 20 as the independent variable.

1.3. Sector differences

We expect the effect of EPU on stock returns to be sector dependent as differences among sectors have already been noted in the literature (see Baker et al., 2016; Pastor & Veronesi, 2012; Phan et al., 2018). More specifically, we expect the effect of EPU to be stronger for sectors that depend more on public spending and for sectors that have strong exposure to regulatory policy changes, such as healthcare and financials.

1.4. Impact in crisis period

We expect the impact of EPU to be higher in period of crisis such as during the GFC or during the Covid crisis. These are periods of strongly elevated uncertainty and Arouri et al. (2016) have demonstrated that the negative impact of EPU is stronger and more persistent in periods of particularly high uncertainty. Hence, the beta linked to the EPU

should be more negative when the sample is a period around those events than when the sample is the full dataset.

2. Data

As we have explained we will work with the EPU index for Belgium developed by Algaba et al. (2020). The data for this index are available on the policy uncertainty website (www.policyuncertainty.com/belgium_monthly.html). As recommended by Rossi (2020), we will work with monthly data because they are less noisy, and volatile compared to daily data. The available data range from January 2000 to September 2022 for the 3 EPU indices related to Belgium (i.e., the national one, and the French and Dutch speaking ones). Despite the data being labelled as first day of the month on the export, the authors have confirmed that they are a monthly average, so they correspond to end-of-the-month data.

For the size analysis, we will work with the BEL 20 and the BEL Small. We retrieve the monthly last price from Bloomberg. The available data for the BEL 20 cover our full period (i.e., Jan. 2000 – Sep. 2022) but the available data for the BEL Small range from December 2002 to September 2022. Concerning the sector analysis, we will work with the Belgian sector indices based on the GICS (Global Industry Classification Standard) classification. The GICS comprises 11 sectors (consumer discretionary, consumer staples, energy, financials, healthcare, industrials, information technology, materials, real estate, and telecommunication). We will use the Euronext BEL Sector for each one of them, except for the real estate sector, because the BEL real estate has been discontinued on Bloomberg since February 2016 and data are not available for it between January 2016 and September 2022 on Yahoo Finance. But because the real estate sector is an important sector of the Brussels exchange with 3 REITs (Real Estate Investment Trust) in the BEL 20 (i.e., Aedifica, Cofinimmo and WDP) we do not want to exclude it from our analysis. Hence, we will instead use the FTSE EPRA Nareit Developed REITs Belgium Index EUR for the real estate sector. The data for the monthly last price of the FTSE EPRA Nareit Developed REITs Belgium index and the 10 others BEL sector indices come from Bloomberg. The data for the BEL sector indices (except BEL Energy) range from December 2008 to September 2022. For the BEL Energy it ranges from February 2013 to September 2022, and for the FTSE EPRA Nareit Developed REITs Belgium index it ranges from November 2012 to September 2022. We also have to note that all the equity indices we work with are price indices, meaning that they do not account for dividends.

We will also use the reference rates of treasury certificates issued by the Belgian state on the secondary market with a 3-months maturity as the risk-free rate, equivalent to Phan et al. (2018) that use 3-months treasury bills in their analysis to proxy risk-free rate. We have retrieved these rates from the website of the National Bank of Belgium (NBB) at <https://stat.nbb.be/Index.aspx?DataSetCode=IRTRCERT#>.

3. Methodology

We start by computing the returns of the stock indices with the following formula: $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$. Then as Phan et al. (2018) do in their study, we compute the excess returns over the risk-free rate. With ER_t being the excess return for the month t we have: $ER_t = R_t - R_{ft}^{17}$. As explained above, we use the rate of 3-months Belgium treasury certificates to proxy the risk-free rate (R_f).

Then to study the predictability we will use what Phan et al. (2018) describe as the classic predictive model, having the EPU with a lag of one month (i.e., EPU_{t-1}) as the predictor or independent variable and the excess returns of month t (ER_t) as the dependent variable leading to the following equation: $ER_t = \alpha + \beta EPU_{t-1} + \varepsilon_t$. But because in practice it is difficult to assume that the error terms exhibit no serial correlation at all and/or that the errors are homoscedastic (i.e., they have constant variance) the OLS will not be the best linear unbiased estimator (BLUE). Instead, we will use generalized least squares (GLS) estimators that are BLUE even in presence of autocorrelation and/or heteroscedasticity (Taboga, 2021). More specifically, because in practice we rarely know the covariance matrix of the error term given X , we will use what is called the feasible generalized least squares (FGLS) model, where this covariance matrix is estimated. The use of the FGLS method follows the approach used by Phan et al. (2018) in their paper. We will realize all our regressions using Stata.

We begin by testing for heteroscedasticity and autocorrelation. We test for heteroscedasticity with the Breusch-Pagan/Cook-Weisberg test. This test is straightforward to read because it has the null hypothesis (H_0) that there is homoscedasticity (i.e., the variances of the residuals are constant) versus the alternative

¹⁷ To see the tables of returns and excess returns per stock indices see Appendices 26 to 36

hypothesis (H1) that there is heteroscedasticity. We will use a confidence level of 90% meaning that if the p-value is smaller than 10% (the alpha), we reject H0 and accept H1 thus considering that the data exhibit heteroscedasticity. We use an alpha of 10% to be more sensitive to heteroscedasticity. To test for first-order serial correlation we use the Breusch-Godfrey test. We have chosen this test because it is also easy to read. It has H0: no serial correlation vs H1: serial correlation. We also use a significance level of 10% to be more sensitive to autocorrelation. Therefore, if the p-value is smaller than 10% we reject H0 and accept H1, considering that there is first-order autocorrelation. Depending on the results of those tests we specify in Stata whether or not our data exhibit heteroscedasticity and/or autocorrelation to adjust the FGLS regression. For more information about FGLS regression and the process to implement it using the Stata software see Stata (n.d.).

4. Results

4.1. Analysis of the predictive power of EPU on the BEL 20 (January 2000 – September 2022)

Our first analysis is to test the predictive power of the three different versions of the EPU index for Belgium on the excess returns of the national Belgian stock index i.e., the BEL 20. To do so we use the EPU data and the BEL 20 data from January 2000 to September 2022. But because we use a predictive model with the excess returns of the BEL 20 in time t as the dependent variable and the EPU level in time $t-1$ as the independent variable, we actually use the excess return of the BEL 20 from February 2000 to September 2022 and the EPU data from January 2000 to August 2022.

Table 2: Descriptive statistics of the variables of our first sample period

	EPU BEL	EPU ND	EPU FR	ER(BEL 20)
Obs	272	272	272	272
Mean	116,09	113,27	118,92	-0,96%
StdDev	57,71	56,06	61,17	5,33%
Min	49,23	53,54	44,07	-24,51%
Max	512,86	521,37	504,36	21,21%

Note: EPU BEL stands for the national EPU index, EPU ND stands for the Dutch-speaking version and EPU FR stands for the French-speaking version of the index. ER(BEL 20) stands for the excess return of the BEL 20.

Source: Made by the author

We see in the above table that the sample for our first analysis is made of 272 observations. The three EPU indices have relatively close average with the French-speaking version one having the highest. The French-speaking index also has the most volatility, proxied by the standard deviation. The maximum value for the three EPU indices were attained in April 2020 in the midst of the Covid crisis. The mean monthly excess return of the BEL 20 is negative at -0.96%, while the maximum excess return of 21.21% was in the month of November 2020, where the BEL 20 beat its historical record with a monthly return of 20.5%. The lowest excess return for the period of -24.51% was for the month of October 2008 during the GFC.

Table 3: Matrix correlation between the three version of EPU index for Belgium and the excess returns of the BEL 20

	<i>EPU BEL</i>	<i>EPU ND</i>	<i>EPU FR</i>	<i>ER(BEL 20)</i>
EPU BEL	1			
EPU ND	0,98314696	1		
EPU FR	0,98586272	0,93861602	1	
ER(BEL 20)	0,20255025	0,20015378	0,19875453	1

Source: Made by the author

As we have already seen the three versions of the EPU index for Belgium are strongly correlated together but more surprisingly the excess returns of the BEL 20 for the month t are positively correlated with the EPU level of the month $t-1$. This indicates that a rise in the EPU level in month $t-1$ would tend to be related with a rise of excess returns in month t . This is different from what has commonly been found in the literature. For example, Phan et al. (2018) have found negative correlation between excess returns in month t and EPU in month $t-1$ for 14 countries and positive for only two countries. We can also note that the excess returns of the BEL 20 have similar correlation with the three versions of the EPU index, the highest one being with the national index.

For our first regression analysis (i.e., $ER_t(\text{BEL 20}) = \alpha + \beta \text{EPU_BEL}_{t-1} + \varepsilon_t$) we begin by testing if there is heteroscedasticity and autocorrelation. We find no evidence of heteroscedasticity but do find evidence of first-order autocorrelation¹⁸. We thus adjust our FGLS regression to account for serial-correlation in the errors. We see in table 4 below, that we obtain a β coefficient of 0.00023, which means that for a rise of 1 in the Belgian EPU level in month $t-1$ the predicted excess return of BEL 20 in month t rise by

¹⁸ See appendices 39 and 40 for the details of the tests

0.023 percentage point¹⁹. And that coefficient is statistically significant even at the restrictive 1% threshold as the p-value (0.001) is smaller than that threshold. This model means that for an EPU level of 100 in month t-1, the predicted excess return of the BEL 20 in month t is $-3.647 + 100 \times 0.023 = -1.347\%$.

Table 4: FGLS regression $ER_t(\text{BEL 20}) = \alpha + \beta \text{EPU_BEL}_{t-1} + \varepsilon_t$

<code>. xtglm ERBEL20 EPUBEL, corr(ar1)</code>						
Cross-sectional time-series FGLS regression						
Coefficients: generalized least squares						
Panels: homoskedastic						
Correlation: common AR(1) coefficient for all panels (0.2969)						
Estimated covariances	=	1	Number of obs	=	272	
Estimated autocorrelations	=	1	Number of groups	=	1	
Estimated coefficients	=	2	Time periods	=	272	
			Wald chi2(1)	=	10.79	
			Prob > chi2	=	0.0010	
ERBEL20	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
EPUBEL	.0002296	.0000699	3.29	0.001	.0000926	.0003666
_cons	-.0364712	.0091793	-3.97	0.000	-.0544622	-.0184801

Source: Made by the author

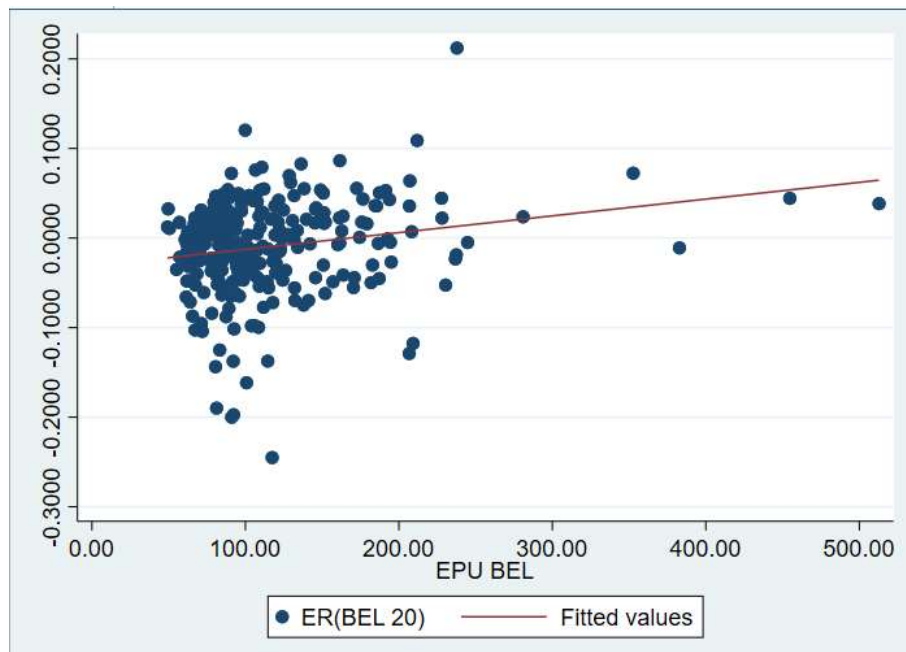
Therefore, and contrary to our first hypothesis we see that the Belgian EPU in month t-1 has a positive and statistically significant impact on the excess return of the BEL 20 in month t. This is different than what has been observed by among others Phan et al. (2018), who testing for 16 countries find negative and statistically significant negative impact of EPU_{t-1} on the excess returns of month t for six countries (they find positive coefficient for seven countries but not statistically significant in their study). But we have to note that some studies have already found some evidence of a positive link between EPU and future stock returns such as Brogaard and Detzel (2015) and Chiang (2022). Chiang (2022) argues that investors that bought a stock in a period of strong uncertainty could be rewarded for that risk taking by receiving higher returns thanks to a risk premium. It can thus explain the positive beta coefficient between the EPU index and the excess returns with a lag of one month.

¹⁹ We need to multiply our coefficients by 100 to express our results in percentage points because in our sample 0.01 equals 1%.

Anyway, one limitation of our model that we can see on the graph 5 below, is that our data are concentrated in a cluster with 75% of the observations with a EPU level between 49.21 and 133. But in that range of EPU levels we have a variety of excess returns ranging from -24.51% to 12.04%. One possibility to improve our model could thus be to eliminate the outliers.

We now turn to the regression analysis of the excess returns of the BEL 20 in month t on the French- and Dutch-speaking versions of the EPU index²⁰. We see in table 5 below, that like the regression with the national index, we have statistically significant and positive betas. The stronger impact is with the Dutch-speaking version of the index, where an increase of 1 unit of the EPU level in month $t-1$ leads to an increase of 0.024 percentage points of the predicted excess return of the BEL 20 in month t . The same increase but with the French-speaking version of the EPU index in $t-1$ would lead to a rise of 0.020 in the excess return of the BEL 20 in t . Thus, we see that the 3 versions of the EPU index have relatively similar impact on the predicted excess return of the BEL 20.

Graph 4: Regression of $ER_t(\text{BEL 20})$ on EPU BEL_{t-1}



Note: The Y-axis represents the $ER_t(\text{BEL 20})$ and 0.01 is equivalent to 1%.

Source: Made by the author

²⁰ Details of the heteroscedasticity and autocorrelation tests as well as of the FGLS regressions are available in appendices 41 to 46

Table 5: Results of the FLGS regressions of $ER_t(\text{BEL } 20)$ on the 3 versions of the EPU index in $t-1$

Excess return (t)	EPU BEL (t-1) Coefficient β	EPU ND (t-1) Coefficient β	EPU FR (t-1) Coefficient β
BEL 20	0,0002296***	0,0002411***	0,0002021***

Note: Need to multiply the coefficients by 100 to have results in percentage points. *, **, *** indicates statistical significance at respectively 10%, 5% and 1%.

Source: Made by the author

4.2. Analysis of the size effect of the predictive power of EPU on the Belgian stock market (December 2002 – September 2022)

We have seen that, contrary to our first hypothesis, a rise in the Belgian EPU indices in $t-1$ should lead to an increase of the excess return of the BEL 20 in t . We will now look whether this effect is different based on the size of companies. To do so, we will compare the predictive ability of the three versions of the EPU index on the excess return of the BEL 20 (constituted of large caps) and of the BEL Small (constituted of small caps). To achieve this, we use the excess returns of the BEL 20 and the BEL Small from January 2003 to September 2022 and the EPU data from December 2002 to August 2022, because we use a lag of 1 month for the EPU data. We expect the predictive power of EPU to be stronger on the BEL Small, as small caps are generally more difficult to value, more volatile, and more subject to speculation, and should thus be more impacted by uncertainty.

Table 6: Descriptive statistics of the variables of our second sample period

	EPU BEL	EPU ND	EPU FR	ER(BEL Sm)	ER(BEL 20)
Obs	237	237	237	237	237
Mean	119,26	117,29	121,24	-0,11%	-0,41%
StdDev	60,97	58,81	64,84	4,76%	5,21%
Min	49,23	53,54	44,07	-19,17%	-24,51%
Max	512,86	521,37	504,36	18,94%	21,21%

Source: Made by the author

We see in table 6, that for this sample period both the BEL 20 and the BEL Small have negative average excess monthly return, but the BEL Small has a higher one at – 0.11% compared to – 0.41% for the BEL 20. The smallest excess return of the period for the BEL Small was for the month of October 2008 and the highest one was in the month of November 2020, as for the BEL 20.

Table 7: Matrix correlation between the 3 versions of the EPU index in t-1 and the excess returns of BEL 20 and BEL Small in t

	EPUBEL	EPUND	EPUFR	ERBEL20	ERBELSm
EPUBEL	1.0000				
EPUND	0.9848	1.0000			
EPUFR	0.9875	0.9450	1.0000		
ERBEL20	0.1753	0.1613	0.1834	1.0000	
ERBELSm	0.1230	0.1121	0.1297	0.8235	1.0000

Source: Made by the author

If we look at the matrix correlation in table 7, we see quite surprisingly that the EPU index in month t-1, whatever the version, is more correlated with the excess return in month t of the BEL 20 than of the BEL Small. Therefore, and contrary to our second assumption, the impact of EPU indices seems to be stronger on large caps than on small ones. Again, all the correlations coefficients are positive, indicating that EPU_{t-1} tend to move in the same direction than ER_t . We can also note that with this sample, it is with the French-speaking EPU index that the correlations are the strongest for both the BEL 20 and the BEL Small.

We then proceeded with testing for heteroscedasticity and serial correlation before estimating the adapted FGLS regressions²¹, whose resultants β coefficients are visible in the table 8 hereunder. We see that, contrary to our second hypothesis, the β linked to EPU indices is also positive when the excess returns of the BEL Small are the dependent variable; and the coefficient are always smaller compared to when the ER(BEL 20) are the dependent variable. For example, according to our model an increase of one in the national EPU level in month t-1 would lead to a rise of predicted excess return for the month t of 0.011 percentage point (pp) for the BEL Small compared to 0.019 pp for the BEL 20. We can also note that the estimated β coefficients linked to the BEL Small are less statistically significant, as they are only statistically significant at the less restrictive 10% threshold, compared to the ones linked to the BEL 20 that are all statistically significant at the 1% threshold. So, it seems that EPU indices, whatever their version, have more impact on the excess returns of the BEL 20 than on those of the BEL Small. Furthermore, we can also note that as was the case with the sample we used for our first analysis, there

²¹ For the details of the heteroscedasticity and auto-correlation tests as well as the estimated FGLS regressions see appendices 47 to 64

seems to have no major differences in the predictive power of the different forms of the EPU index, neither for the BEL 20 nor the BEL Small, as all the betas are relatively close.

Table 8: Results of the FLGS regressions of $ER_t(\text{BEL 20})$ and $ER_t(\text{BEL Small})$ on the 3 versions of the EPU index in $t-1$

Excess return (t)	EPU BEL (t-1) Coefficient β	EPU ND (t-1) Coefficient β	EPU FR (t-1) Coefficient β
BEL 20	0,0001924***	0,0001919***	0,0001794***
BEL Small	0,000111*	0,0001131*	0,0001014*

Note: Need to multiply the coefficients by 100 to have results in percentage point. *, **, *** indicates statistical significance at respectively 10%, 5% and 1%.

Source: Made by the author

4.3. Analysis of the sector dependence of the predictive power of EPU on the Belgian stock market (December 2008 – September 2022)

We will now analyze whether the predictive power of the different versions of the EPU index related to Belgium is indeed sector dependent as we assume in our third hypothesis. We will thus compare the predictive ability of the three types of EPU index on the excess returns of each Belgian sector-based stock indices. To do so, we use the EPU data from December 2008 to August 2022, and the excess returns for the sector indices from January 2009²² to September 2022.

For our sample period, we see in table 9 below that the sector index with the highest monthly average excess return is the consumer discretionary one with 1.53%. The sector index with the lowest average monthly excess return being the telecom sector with -0.31%. We can also note that the maximum monthly excess return was attained by the BEL Energy index with 39.28% in November 2020; while the lowest one was reached by the BEL Utilities with -31.95% in March 2020. If we now look at the correlation matrix in table 10, we see that all correlations between EPU indices and stock indices are again a positive, except for the BEL Telecom (with a correlation with the Belgian EPU of -0.1625 for example). This negative correlation makes sense because the telecom sector is heavily regulated and dependent on laws hence, we can understand that higher uncertainty can tend to lead to lower excess returns in the following month for the BEL Telecom index. What is perhaps less intuitive is that again, with the exception of the BEL Telecom, all the

²² Except for the BEL Energy for which we use the excess returns starting from March 2013 and starting from December 2012 for the FTSE EPRA Nareit Developed REITs Belgium due to data availability

correlations between the sector stock indices and the EPU indices are positive. The highest correlation is with the BEL Industrials index with a coefficient of 0.2349 with the national Belgian EPU index. This strong impact of EPU on the industrials sector is understandable as it is a sector with companies that usually rely strongly on government spending and investment. Surprisingly, and despite being heavily exposed to changes in regulatory policy, the health care sector has a small correlation of only 0.0258 with the Belgian EPU index.

Table 9: Descriptive statistics of the variables of our third sample period

Variable	Obs	Mean	Std. dev.	Min	Max
EPUBEL	165	136.1607	64.03886	62.53787	512.8632
EPUND	165	131.8631	62.66874	58.36417	521.3704
EPUFR	165	140.4583	67.34052	66.63678	504.356
BEL20	165	.0059058	.0454606	-.1615681	.2120708
BELSm	165	.0085505	.0456221	-.1260776	.1894221
Mater	165	.0081272	.0695865	-.192096	.2710505
CDis	165	.015331	.0749239	-.2421104	.3453329
CStap	165	.0085988	.0420239	-.1053897	.1826421
Ener	115	.0086349	.0689735	-.1245098	.3928276
Fin	165	.0077355	.0637328	-.2268904	.2753287
Health	165	.01305	.0588198	-.122572	.1806293
Ind	165	.0075472	.0658413	-.2248634	.2380139
Tech	165	.0124813	.0691141	-.2537245	.2303776
Telecom	165	-.0031511	.0504156	-.149441	.1392833
Util	165	-.00053	.0646706	-.3195226	.1667118
RE	118	.0086907	.0439939	-.1564386	.1032568

Source: Made by the author

Table 10: Matrix correlation between the 3 versions of the EPU index in t-1 and the excess returns of sector-based Belgian stock indices in t

	EPUBEL	EPUND	EPUFR	BEL20	BELSm	Mater	CDis	CStap	Ener	Fin	Health	Ind	Tech	Telecom	Util	RE
EPUBEL	1.0000															
EPUND	0.9894	1.0000														
EPUFR	0.9918	0.9628	1.0000													
BEL20	0.1652	0.1606	0.1663	1.0000												
BELSm	0.0451	0.0412	0.0478	0.7762	1.0000											
Mater	0.1410	0.1364	0.1426	0.7811	0.6711	1.0000										
CDis	0.1775	0.1667	0.1839	0.7387	0.6030	0.5239	1.0000									
CStap	0.1373	0.1316	0.1399	0.5545	0.4231	0.3210	0.4031	1.0000								
Ener	0.0443	0.0383	0.0489	0.5710	0.4753	0.5520	0.4854	0.3569	1.0000							
Fin	0.1479	0.1489	0.1444	0.8486	0.6905	0.7296	0.5537	0.4995	0.6204	1.0000						
Health	0.0258	0.0424	0.0108	0.5445	0.4187	0.2847	0.3232	0.1901	0.1205	0.2309	1.0000					
Ind	0.2349	0.2341	0.2316	0.8269	0.7246	0.7315	0.6078	0.4275	0.5379	0.8129	0.2867	1.0000				
Tech	0.1644	0.1720	0.1548	0.7029	0.6680	0.6553	0.5802	0.2852	0.3396	0.5972	0.4057	0.7083	1.0000			
Telecom	-0.1625	-0.1676	-0.1552	0.3208	0.2787	0.1152	0.2386	0.3582	0.2307	0.2727	0.0579	0.2985	0.0655	1.0000		
Util	0.1639	0.1561	0.1680	0.6240	0.3959	0.5244	0.4489	0.3368	0.3853	0.5050	0.1857	0.5328	0.4338	0.2972	1.0000	
RE	0.0202	0.0062	0.0321	0.5803	0.4947	0.4310	0.4998	0.3761	0.1795	0.3800	0.3546	0.4957	0.4636	0.2914	0.4521	1.0000

Source: Made by the author

After having tested for heteroscedasticity and autocorrelation, we proceeded with the estimation of the adapted FGLS regressions²³ and obtained the β coefficients visible in table 11 below. We see that, as we stated in our third hypothesis, the predictive power of EPU indices on excess stock return is indeed sector dependent. In fact, out of the eleven GICS sectors, we observe a statistically significant predictive power for only six sectors (materials, consumer discretionary, financials, industrials, technology, and telecommunications). We also note that for the BEL Financials it is only statistically significant with the national EPU and for the BEL Telecommunications only with the Dutch-speaking version of the EPU index. All the β coefficients are positive except the ones related to the health care sector (none of which are statistically significant anyway) and those tied to the telecom sector. Moreover, although we expected the financials and the health care sectors to be more impacted by EPU indices, because as pointed by Baker et al. (2016) these sectors are strongly exposed to shift in regulations; we observed a statistically significant impact only between the BEL financials and the national Belgium EPU. Furthermore, we can also note that the strongest predictive power of EPU indices we observe are on the consumer discretionary and industrials sectors, for which we had already observed strong correlations with the EPU indices.

Table 11: Results of the FGLS regressions of ER_t of the Belgian sector stock indices on the 3 versions of the EPU index in t-1

Excess return (t)	EPU BEL (t-1) Coefficient β	EPU ND (t-1) Coefficient β	EPU FR (t-1) Coefficient β
BEL Materials	0,0001437*	0,000145*	0,0001343*
BEL Cons Discr	0,0002393***	0,0002468***	0,0002191**
BEL Cons Staples	0,0000666	0,0000614	0,0000674
BEL Energy	0,0000421	0,0000385	0,0000433
BEL Financials	0,0001271*	0,0001275	0,0001194
BEL Health Care	-0,0000118	-1,16924E-06	-0,0000203
BEL Industrials	0,000214***	0,0002165***	0,0001994***
BEL Technology	0,0001495*	0,0001519*	0,0001389*
BEL Telecom	-0,0001046	-0,0001141*	-0,0000897
BEL Utilities	0,0000787	0,0000532	0,0000962
Real Estate [†]	0,0000138	5,37E-06	0,0000198

Note: Need to multiply the coefficients by 100 to have results in percentage point. *, **, *** indicates statistical significance at respectively 10%, 5% and 1%. [†]For the real estate sector, we use the FTSE EPRA Nareit Developed REITs Belgium index.

Source: Made by the author

²³ For the details of the heteroscedasticity and auto-correlation tests as well as the estimated FGLS regressions see appendices 65 to 163

4.4. Analysis of the predictive power of EPU on the Belgian stock market during crisis periods

We will now analyze the predictive ability of the EPU indices on excess stock returns during crises. We expect this impact to be stronger during these times of high policy-uncertainty. For this analysis we will focus on two periods. The first one will be during the subprime crisis, where we selected a period of 23 months that had Belgian EPU level above the mean level of 116.6 without any interruption. This sample ranges from September 2008 to July 2010. We thus took the EPU levels for these months and the excess returns of the BEL 20 and BEL Small from October 2008 to August 2010 to have a lag of one month. Our second analysis is during the Covid crisis, for which we selected a sample of 17 months with Belgian EPU level above the mean (of 116.6) without any interruption. This period goes from March 2020 to July 2021. We took the EPU levels for these months and the excess returns from the BEL 20, the BEL Small and the 11 sector-based indices from April 2020 to August 2021 to keep a differential of one month.

4.4.1. Analysis of the predictive power of EPU on Belgian stock market during the GFC

We see in table 12 hereunder, that both the BEL 20 and the BEL Small have a negative average excess return for this sample with respectively -0.88% and -0.26%. We also see that, during this period, the BEL 20 had a lower minimum excess return (attained in October 2008) and a lower maximum excess return (attained in April 2009) compared to the BEL Small. We can also note that for this sample it is the Dutch-speaking EPU index that reached the highest level with 268.36 in December 2008. This month saw the highest level attained by Belgian EPU indices before the outburst of the Covid crisis in 2020. It is in December 2008 that then Belgium prime minister Yves Leterme resigned due to its alleged controversial role in the BNP Paribas takeover of the Belgian bank Fortis. We also see that it is the Dutch-speaking EPU index that has the highest average level for that sample, consistent with Algaba et al. (2020) that noted that the GFC was generally more covered in the Dutch-speaking newspapers than in the French-speaking ones in Belgium.

Table 12: Descriptive statistics of our variables during our GFC sample

Variable	Obs	Mean	Std. dev.	Min	Max
EPUBEL	23	174.5016	34.41949	117.4518	237.4071
EPUND	23	178.9036	42.09697	116.0483	268.3599
EPUFR	23	170.0996	29.90064	108.3273	211.1847
ERBEL20	23	-.008823	.0773714	-.2450633	.1089042
ERBELSm	23	-.0026489	.072846	-.191696	.1660591

Source: Made by the author

Table 13: Matrix correlation between the 3 versions of the EPU index in t-1 and the excess returns of BEL 20 and BEL Small indices in t, during our GFC sample

	EPUBEL	EPUND	EPUFR	ERBEL20	ERBELSm
EPUBEL	1.0000				
EPUND	0.9691	1.0000			
EPUFR	0.9378	0.8233	1.0000		
ERBEL20	0.2088	0.1264	0.3028	1.0000	
ERBELSm	0.1311	0.0823	0.1861	0.9118	1.0000

Source: Made by the author

We see in the correlation matrix, in table 13 above, that again the correlations between the EPU indices in t-1 and the stock indices excess returns in t are positive, despite our sample being a recessionary period this time. We can also note that the correlation is stronger with the BEL 20 than with the BEL Small, whatever the version of the EPU index we are looking at. In addition, we also see that the correlations are the highest with the French-speaking version of the EPU and the lowest with the Dutch-speaking EPU.

We then went on with the heteroscedasticity and autocorrelations tests, before estimating the adapted FGLS regressions²⁴. We can see in the table 14 below that we obtained positive β coefficients for all our regressions, but the only statistically significant one (at 5%) is the one between the French-speaking version of the EPU index in t-1 and the excess returns of the BEL 20 in t. Therefore, for that sample period the French speaking index yields much better results in term of predictive power than the two other versions of the EPU index for Belgium. Nevertheless, this result would need to be confirmed for different samples and over multiple time periods before thinking of labelling the French-speaking

²⁴ For the details of the heteroscedasticity and auto-correlation tests as well as the estimated FGLS regressions see appendices 164 to 181

EPU index as a better predictor of excess stock returns. We also see that for our GFC sample, the EPU index, in whichever version, has no statistically significant predictive ability on the excess return of the BEL Small. Our results indicate that, during this high period of uncertainty due to the financial crisis, if the French-speaking version of the EPU rise by 1 unit in $t-1$, the estimated excess return of the BEL 20 would rise by 0.103pp. Thus, in this high uncertainty sample during the GFC we do get a higher β with BEL 20 when the French-speaking EPU is the predictor than in our first 2 samples, but it is less statistically significant (only at 5% compared to at 1% for our first two samples). We also see in table 15 that the BEL 20 excess returns are more correlated with French-speaking EPU than in our first two samples. Hence, we see that the link between EPU indices (especially with the French-speaking version here) and excess stock returns seem to be stronger in recessionary period, as the less important statistical significance could be a result of the rather small sample size ($n=23$). However, what contradicts our fourth hypothesis is that this link is again positive, meaning that a rise in EPU level should lead to a rise in the excess stock return of the following month.

Table 14: Results of the FLGS regressions of ER_t of the BEL 20 and BEL Small on the 3 versions of the EPU index in $t-1$, during the GFC

Excess return (t)	EPU BEL (t-1) Coefficient β	EPU ND (t-1) Coefficient β	EPU FR (t-1) Coefficient β
BEL 20	0.0007142	0.0003879	0.0010286**
BEL Small	0.0002529	0.0001136	0.0004083

Note: Need to multiply the coefficients by 100 to have results in percentage point. *, **, *** indicates statistical significance at respectively 10%, 5% and 1%.

Source: Made by the author

Table 15: Comparison between the different beta and correlation coefficients linking ER_t (BEL20) and EPU_FR_{t-1} for our three different samples

	Sample 1 (01/00-09/22)	Sample 2 (12/02-09/22)	Sample 3 (09/08-08/10)
Coefficient β	0.0002021***	0.0001794***	0.0010286**
Correlation	0.1987	0.1834	0.3028

Note: Need to multiply the β coefficients by 100 to have results in percentage point. *, **, *** indicates statistical significance at respectively 10%, 5% and 1%.

Source: Made by the author

4.4.2. Analysis of the predictive power of EPU on Belgian stock market during the Covid crisis

The Covid crisis led to unprecedented uncertainty which reflects with the 3 EPU indices available for Belgium reaching their historical peak in April 2020 which was during the first lockdown decided in Belgium. We see in table 15, that it is the Dutch-speaking EPU index that has the highest maximum level, but the French-speaking EPU index has a higher average, because as explained by Algaba et al. (2020), the Covid crisis was generally more talked in the French-speaking Belgian press. We also see that, except for the BEL Telecommunications, all the other stock indices have a positive monthly average excess return for that sample, which was not the case for our GFC sample. It can partially be explained by the fact that in November 2020, some Belgian stock indices, like the BEL 20, beat their historical record. Moreover, we can note that the stock index with the highest monthly excess return, in that sample, is the BEL Energy with 39.28% in November 2020. The index that reached the lowest monthly excess return in this sample period is the BEL Consumer Discretionary, with -15.01% in October 2020.

Table 16: Descriptive statistics of our variables for our Covid crisis sample

Variable	Obs	Mean	Std. dev.	Min	Max
EPUBEL	17	259.8415	105.5234	145.6452	512.8632
EPUND	17	241.0524	108.2806	141.6801	521.3704
EPUFR	17	278.6307	105.3456	145.86	504.356
ERBEL20	17	.0309631	.0553217	-.0524675	.2120708
ERBELSm	17	.0260821	.0561509	-.0543033	.1894221
Mater	17	.0434966	.0749397	-.0473735	.2710505
Cdis	17	.0631294	.1202171	-.1500969	.3453329
Cstap	17	.0250148	.0674104	-.0726124	.1826421
Ener	17	.014667	.1146471	-.1114556	.3928276
Fin	17	.0410338	.0752361	-.0589074	.2753287
Health	17	.0139235	.0640682	-.1020906	.1108404
Ind	17	.0538356	.0618254	-.0582921	.2080806
Tech	17	.0384075	.0789993	-.1019344	.2285421
Telecom	17	-.0030878	.0488241	-.0748743	.0978245
Util	17	.0277334	.0497705	-.0554571	.1513967
RE	17	.0221803	.0417393	-.0923818	.0948732

Source: Made by the author

Our Covid sample is the first one where we observe negative correlation coefficients between EPU indices in t-1 and several stock indices' excess return in t, as visible in table 16. Indeed, we see negative correlations between EPU indices and BEL Small, BEL

Materials, BEL Consumer Discretionary, BEL Energy, BEL Telecommunications and FTSE EPRA Nareit Developed REITs Belgium index. As well as negative correlations between Dutch-speaking EPU and BEL Financials and between French-speaking EPU and BEL Industrials, but those last two correlation coefficients are near zero. The strongest negative correlations are between EPU indices and the BEL Telecommunications, with coefficients around -0.33. And the highest correlations are between EPU indices and BEL Technology as well as BEL Utilities with coefficients around 0.21. This indicates, that during our sample period, a rise of EPU indices in t-1 would tend to lead to a rise of excess return of BEL Utilities but a fall of excess returns of BEL Telecommunications.

Table 17: Matrix correlation between the 3 versions of the EPU index in t-1 and the excess returns of BEL 20, BEL Small and Belgian sector indices in t, during our Covid crisis sample

	EPUBEL	EPUND	EPUFR	ERBEL20	ERBELSm	Nater	Cdis	Cstap	Ener	Fin	Health	Ind	Tech	Telecom	Util	RE
EPUBEL	1.0000															
EPUND	0.9883	1.0000														
EPUFR	0.9876	0.9520	1.0000													
ERBEL20	0.0581	0.0456	0.0696	1.0000												
ERBELSm	-0.2060	-0.2001	-0.2070	0.8840	1.0000											
Nater	-0.0570	-0.0662	-0.0462	0.9064	0.9327	1.0000										
Cdis	-0.1751	-0.1804	-0.1654	0.7450	0.7386	0.6939	1.0000									
Cstap	0.1496	0.1143	0.1823	0.6884	0.6113	0.5652	0.4077	1.0000								
Ener	-0.0660	-0.0845	-0.0452	0.8682	0.7843	0.7278	0.7447	0.5413	1.0000							
Fin	0.0034	-0.0140	0.0213	0.9437	0.8560	0.8268	0.7821	0.6940	0.9205	1.0000						
Health	0.1913	0.2269	0.1499	0.4866	0.3176	0.3803	0.1242	0.1403	0.2441	0.2213	1.0000					
Ind	0.0235	0.0484	-0.0026	0.8303	0.8238	0.7772	0.7881	0.5142	0.7511	0.8317	0.2925	1.0000				
Tech	0.2134	0.2211	0.2002	0.8459	0.7579	0.8664	0.5902	0.3467	0.6435	0.7109	0.6523	0.6900	1.0000			
Telecom	-0.3342	-0.3566	-0.3030	0.2809	0.3548	0.2967	0.3468	0.1824	0.3479	0.3002	-0.1199	0.3293	0.0015	1.0000		
Util	0.2185	0.2308	0.2005	0.7522	0.6961	0.7362	0.5231	0.7254	0.5623	0.6674	0.3501	0.6740	0.6498	0.1546	1.0000	
RE	-0.1752	-0.1736	-0.1726	0.3983	0.2549	0.3318	0.5103	0.1150	0.3382	0.3001	0.3581	0.4723	0.3584	-0.0518	0.4134	1.0000

Source: Made by the author

Afterwards, we did test our sample data for heteroscedasticity and first-order serial correlation, before estimating the adapted FGLS regressions²⁵. We see in table 17 below, that several of our estimated betas are negative. This is the case for β coefficients related to BEL Small, BEL Materials, BEL Consumer Discretionary, BEL Energy, BEL Telecommunications and the FTSE EPRA Nareit Developed REITs Belgium index. It is also the case for the β related to the Dutch-speaking EPU with the BEL Financials as the dependent variable, but all the beta coefficients related to the BEL Financials are very close to zero. So, it seems that during the pandemic, increases in the EPU level negatively impacted the excess returns of some stock indices during the following month, as was already indicated by some negative correlations.

Nevertheless, none of our estimated β coefficients for our Covid sample, are statistically significant, even at the less restrictive 10% threshold. Hence, we can not really make

²⁵ For the details of the heteroscedasticity and auto-correlation tests as well as the estimated FGLS regressions see appendices 182 to 298

conclusions about the impact of the EPU indices on the excess stock returns during the Covid crisis. With our model and our sample choice, the three versions of the EPU index for Belgium have no predictive power on excess stock returns during our Covid sample period. One limit of our Covid analysis is the small size of our sample, with only 17 observations it is smaller than the recommended 30 observations to have a reliable sample. But it is because we worked with monthly data and there is no two- and half-year period of non-stop higher than average uncertainty. We could have worked with daily or weekly data, but it would lead to other problems, such as more noise and volatility in the EPU data. Anyway, the Belgium EPU data are only available by month.

Table 18: Results of the FLGS regressions of ER_t of the BEL 20, BEL Small and sector indices for Belgium on the 3 versions of the EPU index in $t-1$, during the Covid crisis

Excess return (t)	EPU BEL (t-1) Coefficient β	EPU ND (t-1) Coefficient β	EPU FR (t-1) Coefficient β
BEL 20	0,0000305	0,0000233	0,0000365
BEL Small	-0,0001096	-0,0001038	-0,0001104
BEL Materials	-0,0000405	-0,0000458	-0,0000328
BEL Cons Discr	-0,0001995	-0,0002003	-0,0001887
BEL Cons Staples	0,0000956	0,0000711	0,0001167
BEL Energy	-0,0000717	-0,0000895	-0,0000492
BEL Financials	0,00000245	-0,00000973	0,0000152
BEL Health Care	0,0001161	0,0001343	0,0000912
BEL Industrials	0,00000915	0,00000948	0,00000853
BEL Technology	0,0001597	0,0001613	0,0001502
BEL Telecom	-0,0001546	-0,0001608	-0,0001404
BEL Utilities	0,000103	0,0001061	0,0000947
Real Estate [†]	-0,0000693	-0,0000669	-0,0000684

Note: Need to multiply the coefficients by 100 to have results in percentage point. *, **, *** indicates statistical significance at respectively 10%, 5% and 1%. [†]For the real estate sector, we use the FTSE EPRA Nareit Developed REITs Belgium index.

Source: Made by the author

Conclusion

Testing the predictive power of the 3 Belgian indices on the excess stock returns of the BEL 20 from January 2000 to September 2022, we do find a statistically significant link but in contradiction to our first hypothesis as this link is positive. It means that based on our study, an increase in the EPU index for Belgium (in whatever version) in month $t-1$, should lead to an increase in the excess returns of the BEL 20, in the following month t .

We then went on to test if there is a size difference on the predictive ability of EPU indices, by comparing the predictive power on the excess returns of the BEL 20 to those of the BEL Small. We do find that indeed there is a difference but contrary to our second assumption, the predictive power seems to be stronger on the BEL 20 than on the BEL Small as the beta coefficients linked to the BEL 20 are higher and more statistically significant. The correlations between the EPU indices and the excess returns with a lag of one month are also higher for the BEL 20 than for the BEL Small. Again, the link is positive, meaning that a rise in Belgian EPU indices should lead to a rise in the excess returns of both the BEL 20 and the BEL Small in the following month. And the increase in the excess returns due to an increase of EPU level should be higher for the BEL 20 than for the BEL Small.

Our third analysis confirmed our third hypothesis that indeed EPU's predictive ability is sector dependent. Not all beta coefficients are statistically significant but all those which are significant are also positive, except for the one between excess returns of the BEL Telecom and the Dutch-speaking EPU which is negative but almost not statistically significant with a p-value of 0.098. We do find statistically significant and positive beta coefficients for the regressions having whatever version of the EPU index as the predictor and having the following sectors' excess returns as the dependent variable: materials, consumer discretionary, industrials and technology. We also find a positive and statistically significant beta between the national Belgium EPU and the BEL Financials, but not with the two regional versions of the EPU index. Nonetheless, the three regressions with the excess returns of the BEL Financials as the dependent variable have similar statistical significance as their p-value are very close to 10% (0.098 with the national EPU, the only one significant at the 10% threshold, 0.105 with the Dutch-speaking EPU and 0.102 with the French-speaking EPU). The differences in statistical significance are stronger in the regressions using the excess returns of the BEL Telecommunications as the dependent variable; with the Dutch-speaking EPU being the

only statistically significant predictor at the 10% threshold with a 0.098 p-value compared to 0.124 with the national EPU index and 0.167 with the French-speaking index. However, this is not sufficient to claim that the Dutch-speaking EPU is a better predictor, especially since the national EPU yields better results with the BEL Financials. Furthermore, we can note that the EPU indices seem to have the strongest predictive power on the BEL Consumer Discretionary and the BEL Industrials, being the only ones statistically significant at the more restrictive 1% threshold (except for the BEL Consumer Discretionary with the French-speaking EPU with a p-value of just 0.01) and having the largest beta coefficients.

In our fourth analysis, we explored the predictive power of EPU during two crisis periods, namely the GFC and the Covid crisis. Looking at the predictive power of the three versions of the EPU index for Belgium on the excess returns on the BEL 20 and the BEL Small, during our GFC sample, the only statistically significant beta we obtain is between the French-speaking EPU in $t-1$ and the BEL 20's excess returns in t . And again, that coefficient is positive, like all the correlations for that sample. Which seems to indicate that during a period of elevated uncertainty, like our GFC sample, a higher level of EPU index in month $t-1$ seem to yield a higher excess return in month t . Now looking at our Covid sample, we did not find any statistically significant beta, possibly due to our small sample size ($n=17$). But it was our first sample where we observed negative correlations between the EPU indices and several excess stock returns. For these stock indices where we observe negative correlations between their excess returns and the three EPU indices (BEL- Small, Materials, Consumer Discretionary, Energy, Telecommunications and FTSE EPRA Nareit Developed REITs Belgium index) we also have negative beta coefficient, although not statistically significant. It seems to indicate that for these indices, during the high uncertainty period of our Covid period sample, higher EPU level in $t-1$ would lead to smaller excess returns in t . This is different from what we had observed in our sector analysis with a broader and more varied sample (December 2008 – September 2022), where only the BEL Telecommunications had negative beta coefficients (with the only statistically significant one being with the Dutch-speaking EPU at 10%). Thus, it looks like the link between EPU indices and stock returns can be more often negative in period of constant elevated uncertainty than in periods where uncertainty evolves in a wider range. But this is a topic that would deserve to be explored further by other studies.

Concerning the version of the EPU index to use when making studies about Belgium, if choosing only one we would advise to go with the national one, as no version of the EPU index yield constantly significantly better results.

To sum up, we have seen that rise in EPU indices can predict higher excess return in the month after. This effect seems to be more important for large caps than small caps. This effect also varies among sectors and is for instance more important for the consumer discretionary and the industrials sectors. This positive effect can seem counterintuitive, but it can make sense as someone who bought stocks after a month that had seen uncertainty rise, receives a positive risk premium to compensate him for the policy uncertainty risk taken, and thus has a positive excess return after that month. We also note that this effect can be altered in crisis periods as it is often negative in our Covid sample (despite not statistically significant) but not in our GFC sample.

The predictive power of EPU indices on Belgian stock market is a topic that would deserve to be deepened, perhaps using different methodology. One limitation of our study is also that we use only simple regressions. It could be a good idea to make multiple regressions with control variables, such as GDP growth, unemployment, inflation rate, etc., to be sure to only capture the effect of the EPU index on the stock returns. In that case it would be important to be aware of potential multicollinearity problems. Another idea is to test the predictive power of EPU on excess returns with different lags (e.g., 2 months, 3 months, etc) to see if the effect is different, as well as to test it with no lags, to see if in that case the effect is negative or still positive most of the time.

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Abstract :

This master's thesis aims to study the impact of economic policy uncertainty, through the 3 versions of the EPU index for Belgium, namely the national, the French-speaking and the Dutch-speaking ones, on the Belgium stock market. In addition to the study of the predictive power of EPU indices on Belgium's national stock index (i.e., the BEL 20), we also studied whether this effect is size-dependent and sector dependent, as well as whether the predictive power is different during crisis periods. For all our analyses we worked with a lag of one month, using the excess stock returns of the month t with the EPU data of the month $t-1$.

Studying the predictive power of EPU indices on the BEL 20 between January 2000 and September 2022 we found a statistically significant impact. But contrary to our first hypothesis it was a positive impact, meaning that when the EPU level rose in month $t-1$, the excess stock returns in month t tended to rise. Concerning the size effect, we studied the predictive power of EPU indices on the BEL 20 and BEL Small excess returns between December 2002 and September 2022. Again, we found a positive impact on both stock indices, but contrary to our second hypothesis, the impact on large caps (i.e., the BEL 20) seems to be more important than on small caps (i.e., the BEL Small), as the beta coefficients linked to the BEL 20 are greater and more statistically significant than those linked to the BEL Small. For our third analysis, we regressed the excess returns of the Belgian sector indices on the EPU indices, between December 2008 and September 2022, to study whether the predictive power is sector dependent or not. We found that indeed, as we assumed in our third hypothesis, it is well sector dependent. Again, almost all the beta coefficients are positive, and the strongest impact is on the consumer discretionary and the industrials sectors. For our last analysis we wanted to study the predictive power of EPU indices during crises. To do so, we used two samples, one for the Subprime crisis between September 2008 and August 2010 and the second for the Covid crisis between March 2020 and August 2021. For our GFC sample we found that all the beta coefficients were positive but only one was statistically significant (between the BEL 20 and the French-speaking EPU). And for our Covid sample we found some positive and some negative links, but none were statistically significant. Moreover, in all our analyses we found no major and constantly better predictive power between the different versions of the EPU index for Belgium.

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