

Louvain School of Management

The idiosyncratic component of stock returns and its relationship with macroeconomic variables in the U.S. market

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Abstract

The key objective of the present study is to investigate the idiosyncratic component of stock returns and its relationship to macroeconomic variables in the U.S. market throughout the examined period from 1990-2017.

On the one hand, along the same lines as previous authors, we found that idiosyncratic volatility increased until the 1990s and strongly increased in 2000, primarily due to the emergence of the Internet bubble. Furthermore, we also noticed a surge during the subprime crisis period in 2008.

On the other hand, we investigated the relationships between idiosyncratic volatility and the industrial production index, unemployment rates and money supply. We found them to be significant, and we explain them during the second part of this thesis.

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1) Introduction

In this paper, we focus on the relationship that may exist between the idiosyncratic component of stock returns and the selected macroeconomic variables of the U.S. stock market (gross domestic product, unemployment rate and M3 money supply). Our work is organised in various parts to best meet the thesis's research question.

First, we examine the idiosyncratic-volatility behaviour in the U.S. stock market throughout the selected time period. Then, we investigate the relationship that may exist between this idiosyncratic volatility and the selected macroeconomic variables of the U.S. stock market. Both of these analyses are made from 1990 to 2017.

In the first part, we found a surge in the idiosyncratic-volatility level during the Internet bubble at the end of the 1990s and during the subprime crisis of 2008. In the second part, we explain the relationship between this idiosyncratic volatility and the industrial production index, money supply and unemployment rates.

2) Literature Review

a) Introduction

The interaction between idiosyncratic risk and macroeconomic variables plays an ever more important role in macroeconomics and finance, as mentioned in the research of Storesletten, Telmer and Yaron (2004). We organised the literature review by first explaining risk in the stock market. In fact, throughout this review, we believe it is significant to state the authors' thoughts about risk in the stock market, and more precisely, the idiosyncratic-risk studies. We will divide our review into two main sections.

In the first section, we will discuss the predictive power of a stock return's idiosyncratic volatility. We will also try to provide enough evidence of its periodical rising throughout recent decades. Finally, we will highlight idiosyncratic-risk determinants that should explain major changes in idiosyncratic volatility across time.

In the second section, we will focus our research on the macroeconomic variables that may influence the stock market's behaviour or that may be affected by the stock market's behaviour. We will provide an overall view of firm-specific risk variation resulting from different macroeconomic variables, and later, we will conduct a more in-depth analysis with some of these variables.

b) Risk in the stock market and possible returns

In this section, we briefly discuss both risk in the stock market and expected returns investigations. This relation between return and risk is constantly argued in the studies that we read.

Fama (2009) considered the extent to which the price of the common stock in the past could be devoted to obtain significant predictions regarding future stock prices. He assumed that the behaviour of security historical prices contains disclosures about its future trends.

By contrast, the Random walks theory says that the series of changing prices has no memory to predict future stock returns; they follow a 'random walk'. Hence, historical prices cannot be used to predict future share prices – which is to say that share prices move randomly and are unpredictable over time. Maurice Kendall (1953) added that each outcome is independent of historical share prices. Consequently, historical prices cannot predict future trends.

Chen, Roll and Ross (2012) investigated the influence of economic variables on stock market returns, and examined asset prices' impacts later on. They also stated that asset prices are supposed to respond to economic news by a price variation. Moreover, they added that various events impact the movements of stock prices differently based on whether the events were active or passive. Ben-Horim and Levy (1980) further investigated stock market risk. Throughout their research, they claimed that the decomposition of security risk into idiosyncratic- and systematic-risk components came from the capital asset pricing model. Moreover, they stated that while the diversification effect within a portfolio of stocks can reduce firm-specific risk, systematic risk cannot be further diversified by this bias.

Our research regarding the expected return in the stock market leads us to say that the movements of stock returns are difficult to predict. Dimitriou and Simos (2010) investigated the relation between stock returns and volatility in the largest international stock markets throughout time. Goyal and Santa-Clara (2003) found a positive relation between average stock variance and the market return. They also added that, in the stock market, there is a trade-off between risk and return. When authors spoke about risk in the paper, they stipulated

that the risk measure includes idiosyncratic risk rather than only systematic risk. Furthermore, Brown and Ferreira (2003) divided the risk of equity returns into two distinctive parts: systematic risk, which is tied to market return and cannot be diversified by the content of a portfolio's stocks; and firm-specific risk, which can benefit the diversification effect that investors utilise for minimising the portfolio risk regarding their expected returns. Later on, Ang, Hodrick, Xing and Zhang (2006) added that high past exposure to innovations stocks in aggregate market volatility earned low future average returns. Robert F. (1997), in his review, investigated the relation between volatility and expected returns by setting a model that can duplicate the main features of the expected return and volatility relations that were observed.

c) Portfolio diversification

In this part, we investigate the portfolio diversification effect, which is a way to decrease portfolio risk by either keeping the same expected portfolio return or increasing this return while maintaining the same portfolio risk.

Wagner and Lau (1971) researched the diversification effect on risk, and concluded that investors who hold riskier stock portfolios should expect higher returns than risk-averse investors. Moreover, they added that investors could reduce risk without losing expected returns by diversifying stocks within portfolios. Hence, they demonstrated that a low-risk portfolio's rate of return is lower than a riskier portfolio's rate of return. Furthermore, Beste, Leventhal, Williams and Lu (2002) highlighted the Markowitz model, and demonstrated that optimal portfolios are built to reduce diversifiable risk as much as possible. These optimal portfolios provide the best possible expected level of return for a given level of risk. In other words, they are the most efficient portfolios, with an optimum level of risk versus return. In reality, investors do not hold perfectly-diversified portfolios for several reasons.

d) Idiosyncratic volatility

i) Power

Concerning the power of idiosyncratic volatility, a wide range of authors, such as Malkiel and Xu (2002), argued that stocks' firm-specific volatility should be positively linked to their respective expected rates of return. Moreover, Jones and Rhodes-Kropf (2003) suggested that investors should also be rewarded in the form of a risk premium for taking the risk to hold high idiosyncratic-volatility stocks in their portfolios. As Dimson, Marsh and Staunton (2002) said, the risk premium is the incremental return that investors require for holding risky securities rather than risk-free ones.

Later on, a large number of literatures indicate that idiosyncratic volatility is positively linked to expected returns, for example, Levy (1978) and Merton (1987) found a positive relation between idiosyncratic risk and expected rates of return. Malkiel and Xu (2002) claimed that stocks that are expected to have high idiosyncratic risk earn high returns in the cross-section. Barberis and Huang (2001) argued that stocks with high idiosyncratic volatility should have higher expected returns.

In contrast, Ang, Hodrick, Xing and Zhang (2009) theorised that, for developed countries, stocks with high recent, average idiosyncratic volatility tend to gain lower average returns than low idiosyncratic-volatility stocks may have. They consequently stated that there is a negative link between idiosyncratic volatility and expected returns. Furthermore, the negative impact is more significant due to a high idiosyncratic volatility in the U.S. market compared to other countries. As a result, strong idiosyncratic-volatility stocks tend to have low respective returns. Moreover, Jones and Rhodes-Kropf (2003), with their samples, examined the reason that stocks with high idiosyncratic volatility had low average returns on the whole.

To continue, Chen and Petkova (2012) helped to identify a missing risk factor in the Fama and French model, this factor helps to explain the idiosyncratic-volatility puzzle. With this factor, they are able to demonstrate that high idiosyncratic-volatility stocks have low returns in their study.

Furthermore, Guo and Savickas (2004) assessed the predictive power of idiosyncratic volatility for the group of 7 (G7) countries' stocks. They noted that, for these countries, the combined idiosyncratic and stock-market volatilities formed a relevant stock-market return predictor. They also pointed out that idiosyncratic volatility and stock-market volatility taken separately do not offer meaningful stock return forecasting. A short time later, the same authors, Guo and Savickas (2006), conducted an in-depth investigation into this volatility in these countries, and claimed that idiosyncratic-volatility changes provide a suitable proxy for investment-opportunity changes over time. Goyal and Santa-Clara (2003) demonstrated that idiosyncratic risk drives stock-market forecasts. Firm-specific risk subsequently explains the majority of average stock-risk variations across time.

ii) Trends and behaviour

Now that we explained the idiosyncratic volatility of stock returns, we investigate this phenomenon over the period 1990-2017. This time period will also be used later in our methodology. Furthermore, through our investigation, we aim to determine the possible increase or decrease in this time horizon that authors put forward.

Bekaert, Hodrick and Zhang (2009) claimed that idiosyncratic volatility is highly correlated across developed countries, and this correlation has increased over time. The correlation effect grows from strength to strength when idiosyncratic variability and market-wide variability are raised in the US.

Xu, Y and Malkiel (2001) studied idiosyncratic-volatility behaviour during the post-war period. They considered several reasons for the rise in idiosyncratic volatility in recent decades. Initially, they observed that this rise is linked to the financial institutions' share numbers in the respective stock markets. Moreover, they completed their study by adding that there is a positive link between firm-specific volatility and expected earnings growth. Furthermore, Campbell, Lettau, Malkiel and Xu (2001) investigated stocks' return volatilities. More precisely, the paper's purpose was to deliver historical volatility movements. Authors focused on three different volatility levels: firm, industry and market levels. For the 1962-1997 sample period, there was a positive idiosyncratic-volatility trend. Over this period, they observed an increase in firm-level volatility, while there were no

similar trends about industry and market volatility. Moreover, they added that all three volatilities moved together, which helped them to predict gross domestic-product (GDP) growth. Malkiel (2001) investigated the reason firm-specific volatility has increased in recent decades. One reason was the presence of institutional investors in the stock market. These types of shareholders subvert the market's volatility when they go either long or short in the stock market.

Fink, Fink, Grullon and Weston (2010) analysed the idiosyncratic volatility for the Internet industry more precisely during the boom period, and observed an increase on the U.S stock market. Authors also said that, during the Internet bubble, young firms' numbers increased and led to a higher idiosyncratic risk in the market. Considering that the age of the firm is a determinant of possible idiosyncratic volatility, they added that depending on the number of young firms in the market, authors are able to forecast the idiosyncratic-volatility behaviour for the next period. At that moment, they observed an increased proportion of young firms in the market, which could be an explanation for this rise in idiosyncratic volatility. At the same time, the increasing number of firms going public contributed to the increase in idiosyncratic volatility.

In this article, Brandt, Brav, Graham and Kumar (2010) observed that, during the year 2000, firm-specific volatility decreased significantly. Moreover, they added that the effect is most obvious in low stock-price firms and corporates with limited institutional ownership. Furthermore, they claimed that trends are increasingly evident among low-priced stocks that are first held by retail investors and with a high level of retail trading. In addition, they demonstrated that price changes through the use of trading activities have a real influence on increases in idiosyncratic volatility. They concluded their study by saying that rises or falls in idiosyncratic-volatility levels are essentially due to retail investors' behaviour in the low-priced stock market. They demonstrated an idiosyncratic-volatility peak five times larger than that of the Internet boom in the 90s. While other authors argued that this strong increase is because of public firms' characteristic changes, many others claimed that it was driven by the changing sentiments of traders. Moreover, in the paper, they presented evidence illustrating that public firms' market-wide decline in maturity can explain most of the firm-specific risk increases during the Internet bubble.

Bekaert, Hodrick and Zhang (2010) investigated idiosyncratic-volatility trends with a sample that extended right up to 2008. On the one hand, they noted that there are no significant idiosyncratic-volatility trends across the world. On the other hand, they found that cash-flow variables, various business-cycle variables and market-wide volatility are the most important determinants of the time variation in the aggregate idiosyncratic volatility in the US. In time crises, they observed an aggregate idiosyncratic volatility that was considerably higher than the sample average. In fact, in times of crisis, firm-specific volatility is constantly higher than in “normal periods”. Moreover, authors also added that idiosyncratic variances are much more highly correlated across countries during crises periods.

iii) Determinants

We investigate the possible idiosyncratic-volatility drivers that authors highlighted in their studies. Bekaert, Hodrick and Zhang (2012) found that cash-flow variables, various business-cycle variables and market-wide volatility are the most important determinants of the time variation in aggregate idiosyncratic variability in the US. Dennis and Strickland (2009), in their study, try to subtract determinants that may influence idiosyncratic volatility in the market. Their analysis focused on the institutional-ownership factor, and supported, by figures, that the type of ownership is a significant idiosyncratic-risk driver in the stock market. Xu and Malkiel (2003) considered the reasons that firm-specific volatility has increased in the stock market in recent decades. One of them is that the National Association of Securities Dealers Automated Quotations (NASDAQ) market’s prominence led to a stronger market volatility. Furthermore, authors concluded that there is a positive relationship between idiosyncratic volatility and expected earnings growth.

1. Type of ownership, Consumer voice, Financial reporting quality, Market competition, Firms' characteristics

This section focuses on how the type of investors or the ownership structure may influence idiosyncratic-volatility behaviour in the U.S. stock market.

Dennis and Strickland (2009) separated their study into a time series and a cross-sectional analysis. Regarding the time-series analysis, they found that idiosyncratic volatility has increased over the past 20 years. Moreover, it is important to note that the institutional-ownership level increased between the 90s and today. The positive link observed between the institutional-ownership level and firm-specific volatility may be the explanation for that rising volatility. Moreover, in the study, they noted that understanding idiosyncratic-volatility behaviour is important because it is part of the total stock-market volatility. Stock-market volatility allows quantitative analysts to value options and other derivative instruments. For instance, it is needed to create pricing-model options.

Li, Nguyen, Pham and Wei (2011) studied the different foreign investors' heterogeneity of contributions that may exist in local stock markets. They highlighted the importance of recognising this heterogeneity among foreign investors, and not only investigating stock-market liberalisation – as some authors have done. In the paper, they noted a negative relationship between large foreign ownership at a firm level and stock-return volatility. Moreover, they added that this relationship has a stronger effect in countries that support shareholder monitoring. Bennett, Sias and Starks (2003) demonstrated that institutions have a great interest in small-cap stocks.

First of all, we start by analysing the influence of consumers' voices on the idiosyncratic volatility of stock returns.

Luo (2007) analyses the impact of negative voices on stock returns. He investigated the relationship that may exist between consumers' negative voices and firms' share prices in the stock market. More precisely, he demonstrated the relevant influences of consumers' negative voices on the decline in firms' future stock returns. This review represents an innovative effort that uses the data of securities prices to disclose poor outcomes resulting

from consumers' negative voices. Furthermore, the author tried to explain how and why reducing these negative voices should stimulate firms' long-term shareholder wealth. Thereafter, he advises corporate managers to allocate more capital resources to marketing expenses in order to simultaneously reduce consumers' negative voices and future idiosyncratic risk.

Then, we are going to focus on the influence of the quality of financial reporting on the idiosyncratic volatility of stock returns and more precisely on the importance of financial information.

Rajgopal and Venkatachalam (2011) investigated the extent to which the quality of financial reporting is a determinant factor of the idiosyncratic-volatility trend over the last four decades. Furthermore, Verdi (2006) investigated the economic implications of enhanced financial reporting. More precisely, he studied the relationship between the quality of financial reporting and investment efficiency throughout the 1980-2003 period. This relationship is even stronger for firms that are facing financial constraints in the market. Moreover, they found that this relationship is stronger for firms with low-quality information environments. Vlastakis and Markellos (2007) explained the relationship between market-related information and stock-market activity. They concluded that market information has a relevant, positive link with historical volatility, which is to say that information has a strong effect on overall market volatility.

Ang, Hodrick, Xing and Zhang (2006) found an anomaly in the form of a negative relationship between future returns and the firm-specific volatility of stock returns. The excessive extrapolation on firm growth or the extrapolation bias could explain this. According to Lakonishok, Shleifer and Vishny (1994), this occurs when investors try to predict the future by relying too heavily on the firm's past growth. Investors may react because of future earnings negative news, and, as a result, cause stock overvaluation.

Furthermore, Panousi and Papanikolaou (2012) reflected on the impact of risk on the valuation of investment projects, and concluded that idiosyncratic risk does not affect it because stockholders are able to diversify their portfolios in order to eliminate it. Moreover, they added that there is a negative relation between firm-specific risk and the listed firms' investment projects.

Vuolteenaho (2002) said firm-level stock returns are driven by cash-flow news, and cash-flow news is positively correlated with shocks to expected returns. Morck, Yeung and Yu (2000) added that the level of information opacity impacted the market volatility within countries. Hence, more information opacity discouraged competitors from entering the market, and would negatively impact firm-specific volatility.

Moreover, authors focused on the relation that may exist between the market competition and the idiosyncratic volatility of stock returns.

Schmidt (1997) suggested that competition has increased in recent decades due to market deregulation and globalisation around the world. We decided to investigate the market's competition effect on idiosyncratic risk, and more precisely, competition in the product market. Campbell, Lettau, Malkiel and Xu (2001) studied the stock market's volatility behaviour at market, industries and firm levels. The authors concluded in the paper that the average stock-return volatility increased between 1962 and 1997. They claimed that the idiosyncratic volatility of stock returns increased during this period, while stock-market volatility remained constant.

The authors concluded that a higher level of competition, deregulation, globalisation and technological innovation within different markets should partly explain the increase in stock-return volatility in any of those markets. Leroy and Porter (1981), and Campbell and Shiller (1988) concluded that there is a link between the competition level and the firm-specific cost shocks.

Gaspar and Massa (2006) investigated the link between a firm's competitive environment and idiosyncratic volatility. The authors argued that the positioning of firms in the business environment could influence a firm's shock impacts. Moreover, they noted that there is a positive relationship between the uncertainty about a firm's future profitability and the market-competition level. They concluded that the rise in product-market competition has highly contributed to recent idiosyncratic-volatility trend increases.

Wei and Zhang (2006) concluded that fundamental variable changes in the market cause return volatilities. Thereafter, they explored the upward origins of stock-return volatility, and noted that stock-market components are the essential origin of stock-return volatility changes

over the past few decades. The volatility of new entrants' stocks may be responsible for the increase of stock-return volatility. Brown and Ferreira (2003) said that there is a link between business cycles and the average return volatility of stocks.

Irvine and Pontiff (2009) state that firm-specific volatilities range from country to country and over time. Furthermore, they explained the extent to which fierce competition in the economy can lead to a higher idiosyncratic risk. Furthermore, in his model, Philippon (2003) demonstrates how price stickiness leads to a relationship between competition and firm-specific risk.

Furthermore, we focus on the influence of firm's characteristics on the idiosyncratic volatility of stock returns. More precisely, we elaborate on the further variables related to a firm's characteristics, such as the age or size of the firm, as well as the growth and fundamentals that influence the idiosyncratic-volatility component of stock returns.

Brown and Kapadia (2007) concluded that idiosyncratic risk has increased after World War II because of the effects of new listing companies. Indeed, the increase in firm-specific risk is due to the rise in the number of volatile firms listed on the stock exchange, which are more volatile according to Brown and Kapadia (2007). Wei and Zhang (2006) claimed that stock-return volatility is changing over time because some firms exit from the market and others enter. Moreover, newcomers tend to have a higher volatility than firms that are already listing on the stock market. Moreover, they added that smaller firms have a tendency to be more volatile than large, listed corporations.

Brown and Kapadia (2005) found that the idiosyncratic-risk increase is due to the fact that an increasing number of volatile or riskier firms are being listed on the stock exchange. To conclude, they explained that growth opportunities, profitability, firm size and industry composition are linked to an increase in idiosyncratic risk. Wei and Zhang (2006) found that stock variance and profitability levels are associated with average stock-return volatility. They added that there is a negative relationship between a firm's age and its average stock-return volatility.

Finally, Pastor and Veronesi (2003) investigated the reasons firms go public. The authors concluded that market conditions are the most important factor in the decision to go

public or not. In their review, they specified that the relevant market-condition factors are the equity premium, expected aggregate profitability and uncertainty. Furthermore, Fink, Fink, Grullon and Weston (2010) argued that firms tend to go public at a young age and therefore enter the market sooner.

Brandt, Graham and Kumar (2010) found that investors' speculative behaviour caused an increase in idiosyncratic volatility throughout the 1990s. Thereafter, they added that low share prices potentially had a high idiosyncratic-volatility trend during the 1990s. This is due to trading by retail investors who dominated low-priced stock markets.

Bekaert, Hodrick and Zhang (2012) add business-cycle variables to the list of determinants of idiosyncratic-volatility changes. Their results identify this corporate variable as an explanation for a large part of idiosyncratic-volatility time variations. The authors claimed that there is no upward trend in firm-specific volatility anywhere in the developed world.

Brandt, Brav, Graham and Kumar (2010) tried to understand the possible drop in the idiosyncratic volatility of stock returns. They demonstrated that the rise in firm-specific volatility was particularly present in stocks with low share prices throughout the 1990s. They observed that retail investors are more driven by making investments in low stock-price firms that are more fluctuant than higher ones. Moreover, split stocks led to a rise in idiosyncratic volatility throughout this period.

Galai and Masulis (1976) argued that firm's managers have a tendency to acquire investment opportunities that increase their firm's idiosyncratic risk.

e) The stock market and macroeconomic variables

In this section, we discuss the relationship that may exist between the stock market as a whole and the macroeconomic variables. To have a suitable proxy for their linkage, we have gathered information about both U.S. and additional markets.

i) The U.S. market

Flannery and Protopapadakis (2002) investigated macroeconomic variables' impacts on the stock market. Previous authors documented significant effects of inflation and money supply on stock returns. Moreover, they added that identifying macro variables that influence aggregate equity returns would benefit market operators. On one hand, these variables may indicate hedging opportunities for investors; on the other hand, they may constitute price factors for risk-averse investors who will thus be sensitive to the movements of macroeconomic variables.

Hamilton and Lin (1996) studied the monthly movements of stock returns and fluctuations in industrial production. They claimed that economic downturns drive the volatility of stock returns. Furthermore, they went deeper in their study by saying that the business cycle explains 60% of the variance in stock returns. Afterwards, they built a model that was permitted to forecast stock volatility and economic changes.

Comincioli (1996) said that the stock market is a leading economic indicator. In his study, the author investigated the relationships between stock prices and the economy in terms of growth. His results indicated that the stock market could help to predict the future of the economy. In addition, he concluded that fluctuations in economic activity are partially caused by stock-price changes, and can help to forecast future stock-market movements, as Hong, Torous and Valkanov (2007) later stated in their paper. Thereafter, Levine and Zervos (1996) added that there is a positive relationship between the stock market and economic growth.

ii) Additional markets

Jaafar and Zulaikha (2013) tried to understand the impact of economic variables on fluctuations in stock prices within the Malaysian market. He concluded that there is a significant relationship between macroeconomic variables and the stock market. More precisely, his study found that there is a 5% level of significance in the relationship between stock prices, money supply (M3) and exchange rates. Furthermore, Kwon and Shin (1999) demonstrated whether current economic activities in Korea can explain stock-market returns. They found that the Korean stock market reflects macroeconomic variables on stock-price indices, and affirmed that stock-price indices are not a leading indicator. On another continent, Abugri (2006) investigated Latin American stock markets, such as Argentina, Brazil, Chile and Mexico. He studied and tried to understand the possible relationship that may have existed between a few macroeconomic indicators and the stock-market returns. He concluded that there are significant macroeconomic factors that have an impact on the Latin-American stock markets.

Liljeblom and Stenius (1997) studied the relationship between the Finnish stock market and macroeconomic volatility with a sample from 1920 to 1991. The results indicated that almost two thirds of the changes in aggregate stock volatility might be related to macroeconomic volatility. Furthermore, the authors also detected a negative relationship between stock-market volatility and trading-volume growth.

By using a 13-year sample, from January 1990 to January 2003, Gan, Lee, Yong and Zhang (2006) demonstrated that the New Zealand stock market might be highly sensitive to global macroeconomic factors. In addition, they examined the relationships between the NZSE40 and a set of macroeconomic variables. Moreover, it is important to note that during this time period the New Zealand Stock Index was driven by the interest rate, money supply and real GDP.

Zakaria and Shamsuddin (2012) concentrated their investigation on an emerging market. Their writing provides further proof to support the existence of the relationship between stock-market volatility and macroeconomic volatilities in the case of the emerging market.

They studied the relationship between stock-market and macroeconomic volatility in Malaysia for five selected macroeconomic variables, namely GDP, inflation, exchange rate, interest rates and money supply, based on monthly data from January 2000 to June 2012. By utilising the Granger causality test, the authors found that only money supply has a significant 5%-level relationship with the stock-market volatility in Malaysia, unlike other variables, which are not significant related to the stock market. Afterwards, they concluded that there was a positive relationship.

iii) The relationship between the stock market and macroeconomic variables

In this section, we will focus on the link between the inflation rate and the stock market.

According to Firth (1979), stock returns and inflation rates should move in the same direction thanks to the Fisher effect, which argues that expected stock returns are equal to the real return plus the expected rate of inflation. Furthermore, Glutekin (1983) investigated the relationship that may have existed between expected stock returns and expected inflation. He claimed that there is a positive relationship between the two, and added that unanticipated inflation has tended to be negatively correlated with fluctuations in stock returns. In contrast, Fama (1981) explained that during the post-war period, there was a negative relationship between stock returns and inflation. He also added that this relationship is related to industrial activity that drives the inflation within a country. Several years later, Lee (1992) confirmed Fama's analysis with his paper.

Kaul (1987) investigated the relationship between stock returns and inflation in different countries, such as the UK, Germany, Canada and the US, during the post-war period. He claimed that securities can be seen as hedging instruments against inflation fluctuations. Furthermore, the author mentioned that this negative relationship was reinforced by countercyclical responses in money supply and demand. Geske and Roll (1983) added, in their paper, that the link exists because of variations in monetary expansion. Moreover, Schwert (1989) worked on a sample from 1857 to 1987 in an attempt to understand the relationship between stock-market rates of return and inflation. His analysis concluded that

stock-return volatility is not a suitable predictor of inflation movements during the war period.

The link between the economic activity growth and the stock market was also pointed to be significant. Indeed, Levine and Zervos (1996) investigated the relationship that may have existed between GDP growth and the stock market. After their analysis, they found that there is a positive relationship. Some years later, Nagaishi (1999) investigated the importance of the Indian stock market, and confirmed the positive link in his study. However, some researchers were not in agreement on the issue. In fact, Deb and Mukherjee (2008) studied this relationship for almost 10 years (1996-2007), and added to the previous analysis that it is a reciprocating relationship, not just a positive one.

Demirgüç-Kunt and Levine (1996) investigated the relationship between long-term economic growth and the stock market. He claimed that stock-market movements are significant for forecasting future economic growth.

Rousseau and Wachtel (2000) studied the relationship that may have existed between the stock market and economic data between 1980 and 1995. They found that economic growth plays an important role in stock-market trends.

Finally, Bilson, Brailsford and Hooper (2001) investigated this relationship and said that local factors rather than global factors are the primary source of variations in equity return in emerging markets.

3) Hypotheses

a) Regarding the idiosyncratic-volatility trend (model 1)

i) Times interval

1. *H1: The idiosyncratic volatility of stock returns increased during the following periods:*
 - a. *H1.1: The idiosyncratic volatility of stock returns increased from the beginning of our period, which is January 1990, until the end of the 1990s.*
 - b. *H1.2: The idiosyncratic volatility of stock returns increased between January 2001 and the end of 2008.*
 - c. *H1.3: The idiosyncratic volatility of stock returns increased between January 2009 and March 2017.*

ii) Significant events

1. *H2: The idiosyncratic volatility of stock returns strongly increased during the following periods:*
 - a. *H2.1: The idiosyncratic volatility of stock returns strongly increased during the Internet bubble, which occurred in the second part of the 1990s until January 2000.*
 - i. *H2.1.1.: The volatility shock is more significant in the tertiary sector.*
 - b. *H2.2: The idiosyncratic volatility of stock returns strongly increased during the subprime crisis from the beginning of 2007 until October 2008.*
 - i. *H2.2.1: The volatility shock is more important in the financial sector.*

c. H2.3: The idiosyncratic volatility of stock returns increased during the Sovereign Debt crisis, which occurred from October 2010 until July 2011.

i. H2.3.1: The volatility shock increased significantly in the public sector.

b) Regarding the relationship between selected macroeconomic variables and idiosyncratic risk (model 2)

- i) The idiosyncratic component of stock returns is positively related to the industrial production index.**
- ii) The idiosyncratic component of stock returns is positively related to money supply in the US.**
- iii) The idiosyncratic component of stock returns is negatively related to unemployment rates in the US.**

4) Theoretical Framework

Researchers have employed different theoretical frameworks to explain idiosyncratic risk and the relationship that may exist between idiosyncratic volatility and macroeconomic variables. These include the capital asset pricing model (CAPM) by Markowitz (1959), the arbitrage pricing theory (APT) developed by Ross (1976) and the Fama-French three-factor model (1992).

a) The CAPM

According to Robert and Merton (1973), the CAPM is one of the more important developments in modern capital-market theory. Built on the model of portfolio choice, which was developed by Markowitz (1959), the CAPM attempts to assess risk and to quantify the relationship between expected return and associated risk. The CAPM is commonly attributed to William Sharpe (1964); however, it was also developed by Linter (1965), Mossin (1966) and Fisher (1972). The model relies on different assumptions, essentially related to investor behaviour and the presence of a single, common risk factor, as explained by Womack (2003). Furthermore, as Fama and French (2004) explained, the model argues that investors choose ‘mean-variance-efficient’ portfolios. In other words, they will maximise expected returns for a given level of expected risk. As a result, the model allows one to predict the expected return if the expected risk is known.

The formula of this model is computed as follow:

$$E(R_i) = R_f + \beta_i [E(R_m) - R_f]$$

Where

$E(R_i)$ = the expected return on an asset i ,

R_f = the risk-free rate,

β_i = beta of asset i ; a measure of systematic risk,

$E(R_m)$ = expected return on the market portfolio that contains all assets,

$E(R_m) - R_f$ = and the market risk premium, which is a measure of the excess return of the market portfolio over the risk-free rate.

Although the CAPM is still used today, and many experts consider it as a reference, it is still subject to theoretical and empirical criticism, primarily due to the fact that investors choose their portfolios according to the Markowitz mean-variance criterion. The CAPM has also been criticised for the additional assumptions that are required, such as homogeneous expectations and the single period nature of the model. It is important to note that the capital market operates only if the assumptions are satisfied. Finally, one important explanation for these criticism is the difficulty to implement validity tests of the model.

Furthermore, some predictions of the model are sometimes not held, as demonstrated, for example, by Black, Jensen and Scholes (1972), based on empirical tests regarding the statement arguing that expected excess return is proportional to the covariance of its return with the market portfolio.

b) The APT

With the APT, Roll and Ross (1980) offer a testable alternative to the well-known CAPM that Linter (1965), Mossin (1966) and Fisher (1972) introduced. In fact, the APT is an alternative to the CAPM; it agrees perfectly with the intuition behind the CAPM. However, there are two major differences between the APT and the CAPM as we can see hereafter in the formula of APT:

$$E(R_i) = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \dots + \lambda_k\beta_{ik}$$

Where

$E(R_i)$ = the expected return on an asset i ,

λ_0 = the expected return on an asset with zero systematic risk,

λ_j = the risk premium related to the j th common risk factor,

β_{ij} = and the pricing relationship between the risk premium and the asset; that is, how responsive asset i is to the j th common factor.

Firstly, the APT allows more than just one factor to predict the expected return. Secondly, the APT demonstrates that any market equilibrium will be characterised by a linear relationship between each asset's expected return and its common factors. In this theory, the expected returns are explained as a linear function of these common factors.

c) The Fama-French three-factor model

Following the previous theories, Fama and French (1992) developed the three-factor model. In their paper, they demonstrated that the beta factor presented in previous theories does not capture all the risk needed to predict the expected return. Their three-factor model states that risk is not only dependent on the market, but is also linked to other risk factors. For instance, they claimed that smaller firms tended to offer greater returns than larger companies. Furthermore, firms with high book-to-market equity ratios (value stocks) appeared to offer lower returns than low book-to-market equity ratios (growth stocks).

Fama and French's analysis investigated the expected return explanation. They were able to explain most of the cross-section of the average stock returns for a period from 1963 to 1990 on the NASDAQ, NYSE and Amex. The Fama and French model explained approximately 93% of the stock-return variations, compared to the CAPM, which explained only 73% of the variations. In their research, they concluded that expected returns of stocks are better explained when other factors are included within the model.

The formula of the model is computed as follow:

$$r_t^i - RF = a^i + \beta_{MKT}^i(MKT_t) + \beta_{SMB}^i(SMB_t) + \beta_{HML}^i(HML_t) + \varepsilon_t^i$$

Where

- r_t^i = The stock return for asset i in time t .
- RF = The risk-free rate.
- MKT_t = The market-risk premium, which is the difference between the market return and the risk-free rate.
- SMB_t = The size factor "Small Minus Big", which accounts for the return difference between small and large companies.
- HML_t = The book-to-market factor "High Minus Low", which is the difference between the value of high and low book-to-market equity-ratio firms.
- ε_t^i = The error term that constitutes the residuals of the regression.

d) Sectoral distribution

Kenessey (2001) explained the importance of separating the overall economy into four sectors. These sectors are quite different from each other, and they can be interesting to analyse separately for comparative analyses. Moreover, he regrouped these sectors by activities as follows: first, primary activities that regroup into agriculture, forestry, fishing and mining; second, secondary activities that regroup into construction and manufacturing; third, tertiary activities, such as transportation, electric, gas and sanitary services, wholesale trade and retail trade; and finally, quaternary activities in which one would find finance, insurance and real estate services, and public administration.

e) Stationarity

To model and regress a time series, stationarity matters and plays a crucial role as it provides stability for the model, on the one hand, and a framework, on the other hand, in which results can describe the time series behaviour. Furthermore, it is also important as it allows for meaningful results to be obtained regarding correlations with other variables. If a time series is not stationary, we cannot rely on the results. To understand why, the example of a time series increasing over time can be used; the sample mean and variance of the time series will grow with the size of the sample, and a bias will exist regarding any result as it will underestimate values.

In order to be stationary, the statistical structure (mean, variance and autocorrelation) of the time series should be constant over time. To determine whether a series is stationary or not, it can be visualised graphically or computed mathematically. Some statistical tests also exist, such as the well-known Dickey-Fuller test, which was developed in 1979 by David Dickey and Wayne Fuller. This test tests the null hypothesis, regarding whether a unit root is present in an autoregressive model, against the alternative hypothesis of stationarity.

When a time series is not stationary, some tools exist to transform it to achieve stationarity. One method consists of using logarithms or square roots of the variables to stabilise the variance, but only to a certain limit, since this method cannot be used for each

type of variable, and sometimes this method alone is not enough to handle the problem of non-stationarity. Another method, which we will use regarding our data, involves differencing the data – transforming the data into period-to-period differences. Thereafter, if the data are still non-stationary, we can do this manipulation another time.

5) Data and methodology

a) Data

i) Sample

Our analysis of idiosyncratic volatility and its relationship with macroeconomic variables in the U.S. market is conducted using data over a 27-year period, starting in January 1990 and ending in March 2017. Using the daily returns of 38 industry portfolios, available on the Fama-French website¹, we can precisely describe the movements of industry stock returns during the selected time period.

We decided to analyse this time period because of significant events that occurred during that time. Firstly, the Internet bubble, which occurred during the 1997-2000 period in the market. Thereafter, the subprime crisis that emerged at the end of 2007 and the sovereign debt crisis in 2010. As investigated in the above literature, idiosyncratic risk had a tendency to increase throughout this period of time. Furthermore, after our analysis, we would be able to verify whether the idiosyncratic components of stock returns increased since 1990.

ii) Selection

We organised our selection into two data sets. First, we selected and downloaded 38 industry portfolios from the Fama-French website². A description of these 38 industries' portfolios are available in the appendix (table 1). The historical daily returns were available from July 1926 to March 2017. Considering our 27-year period, we have observations for 260,946 daily returns, and more precisely, 6,867 return observations for each industry portfolio.

¹ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

² idem

Since we used the Fama and French three-factor model for computing the idiosyncratic component of stock returns, we also acquired the daily risk-factor values for the respective time period. The market-risk premium, the firm size and the book-to-market equity factors are also obtained from the Fama-French website³. Furthermore, these factor's data are available starting from 1927 to 2017. We extracted the data for our period of interest – January 1990 to March 2017 – and we picked up the selected time period's factor values (1990-2017).

These factors are respectively represented in the multiple regression by 'MKT-RF', 'SMB' and 'HML'. To calculate the idiosyncratic component of stock returns, we used Stata software to obtain the residuals. It is important to note that all tests were conducted based on daily data.

Secondly, we selected a few macroeconomic variables that we identified as being potentially linked to the idiosyncratic component of stock returns. Those variables are the industrial production index, the unemployment rate and the money supply. For each of these variables, we selected a number of time series that can act as a proxy. Three of these variables' time series, namely the GDP, the unemployment rate and the M3 money supply, were retrieved from the Federal reserve website⁴.

The data available on these websites covers a variety of time periods. As we are working on the 1990-2017 period, we will only use the data corresponding to this time period. For each macroeconomic variable time series, we have observations corresponding to a 27-year period.

³ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

⁴ <https://fred.stlouisfed.org>

iii) Methodology

1. *Idiosyncratic component of stock returns computation*

a. *The Fama-French three-factor model*

Fama and French built a model by which the reward for a potential risk is dependent not only on the market, as CAPM assumed, but also on different risk factors. Some findings stem from this model, for example, smaller firms tend to offer higher returns than larger companies, or firms with high book-to-market equity ratios (value stocks) offer lower returns, on average, than low book-to-market equity-ratio companies (growth stocks). According to them, the three-factor model explains stock returns more precisely than the CAPM. The Fama French three-factor model is more relevant for the excess return's explanations. By using this model, we will be able to compute the idiosyncratic volatility for our sample.

b. *Motivation for the use of this model*

Guo and Savickas (2004) added, in their study, that there is a close link between Fama and French's book-to-market factor and firm-specific volatility. Moreover, the Fama and French (1992) three-factor model explains a larger portion of the excess return than the other asset-pricing models.

According to Chen and Petkova (2012), we can compute the idiosyncratic risk of stock returns by using the Fama-French three-factor model. In addition, the idiosyncratic component of stock returns can be assessed by computing the error term's standard deviation of the Fama French three-factor model. In fact, idiosyncratic risk can be evaluated from the model's residuals.

Ang, Hodrick, Xing and Zhang (2009) specify that the Fama-French three-factor model is used for computing the idiosyncratic volatility of stock returns.

c. Model description

$$r_t^i - RF = \alpha^i + \beta_{MKT}^i(MKT_t) + \beta_{SMB}^i(SMB_t) + \beta_{HML}^i(HML_t) + \varepsilon_t^i$$

Where

- r_t^i refers to the stock return for asset i in time t ,
- RF is the risk-free rate,
- MKT_t is the market-risk premium, which is the difference between the market return and the risk-free rate,
- SMB_t is the size factor “Small Minus Big”, which accounts for the return difference between small and large companies,
- HML_t is the book-to-market factor “High Minus Low”, which is the difference between the value of high and low book-to-market equity-ratio firms, and
- ε_t^i the error term that constitutes the residuals of the regression.

This is the equation that we used to compute the idiosyncratic component of the stock returns for each of our 38 portfolios. In this formula, we use the ordinary least-squared (OLS) regressions for each selected portfolio. These regressions provide us with the alpha term and the other factors that constitute the Fama-French Model.

For the idiosyncratic-risk computation, we used the Ang, Hodrick, Xing and Zhang (2006, 2009) method. They defined the idiosyncratic volatility for a trading month as the standard deviation of daily residuals from the Fama-French three-factor model, multiplied by the number of trading days of the corresponding month ‘n’ $\left(\sqrt{var(\varepsilon_t^i)} * \sqrt{n} \right)$.

Once we have the idiosyncratic-volatility measure, we perform the regressions for each of the 38 portfolios. Each regression produces residuals that we obtain thanks to statistic software. Using the formula above, we compute the idiosyncratic volatility from month to month for the 38 portfolios that constitute our sample.

2. *Investigating the relationship between idiosyncratic volatility and macroeconomic variables*

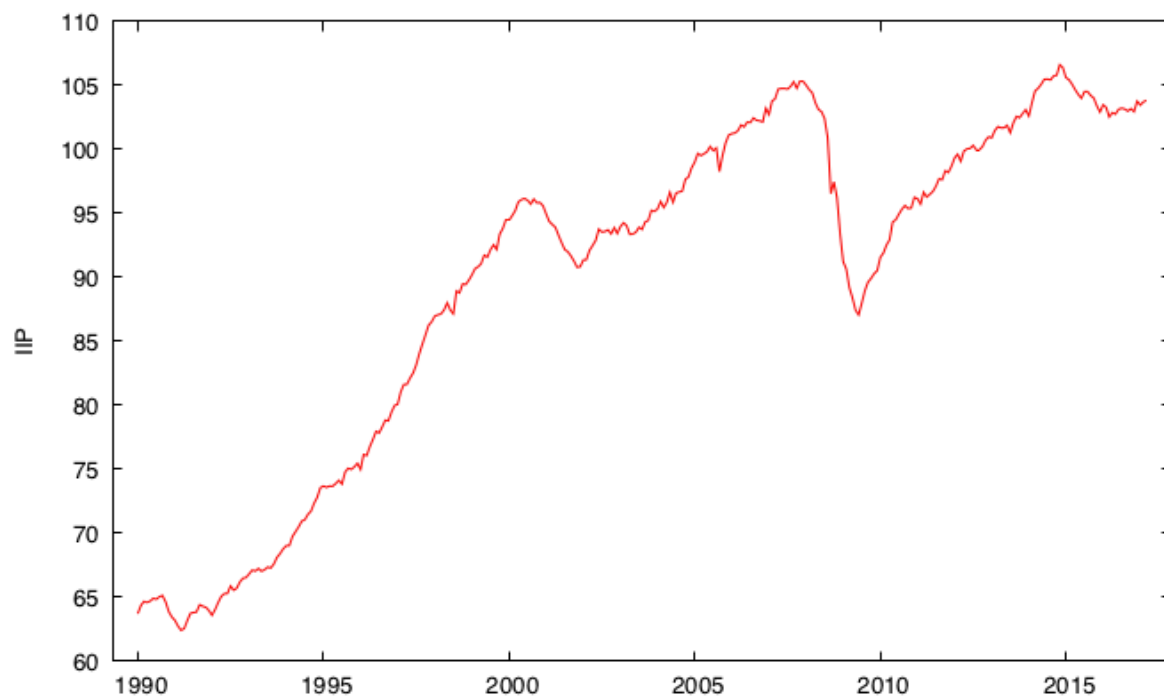
a. *Idiosyncratic volatility and each of the selected macroeconomic variables*

Then, after the computation of the monthly idiosyncratic volatility for our 38 industry portfolios, we are going to focus on the different relations that may exist between the idiosyncratic volatility of our industry portfolios' returns and the three macroeconomic variables that we have chosen, namely the GDP – approximated by the index of industrial production (IIP) – the M3 money supply and the unemployment rate.

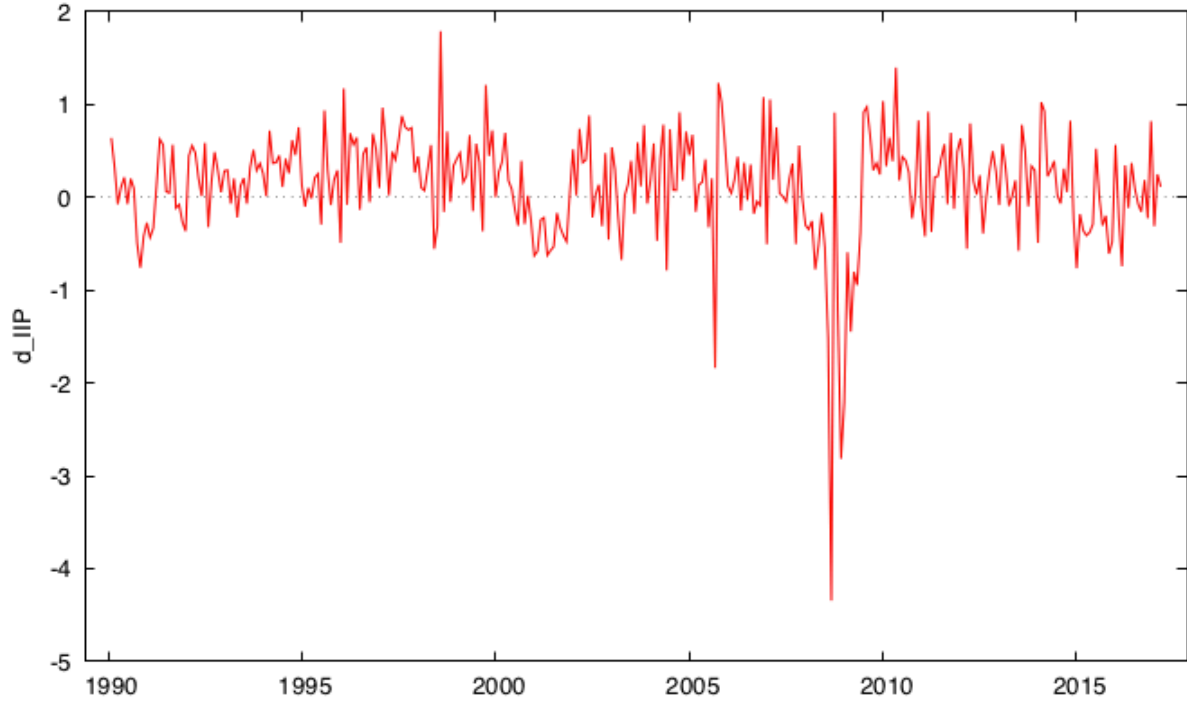
To assess this, we proceed in three steps. Firstly, as we will explain more precisely in the following sections, we regress each of the three macroeconomic variables on the idiosyncratic volatility of each of the 38 industry portfolios, obtaining 38 regressions for each of our macroeconomic variables. Secondly, we analyse all the results of our regressions, saving the coefficients, p-values and significance levels of each regression in three different tables for the three macroeconomic variables. Finally, based on our findings we will distinguish relationships that are significant from those that are not, and then focus on the significant ones in order to analyse the relation and determine whether there is a positive or negative correlation between the variables.

i. The relationship between the GDP and the idiosyncratic volatility of our industry portfolios

We will begin with the analysis of the existence of any relationship between GDP and idiosyncratic volatility. In order to assess this, we will use the IIP as a proxy for the GDP. We have the time series; therefore, before computing our regression, we first verify the stationarity of our variables by inspecting the presence of any tendency. The graph just below represents the evolution of the IIP from 1990 to 2017. It clearly appears that the time series is not stationary.



In order to solve this problem, we make all the required transformations, since they are necessary conditions for obtaining meaningful results. We use the method of differences and we get the new graph presented hereafter:



Now that our time series data appear to be stationary, we regress the monthly U.S. IIP growth rate, which is our dependent variable, on the monthly idiosyncratic volatility of our industry portfolios' returns, which is our independent variable. We obtain the following equation:

$$IIP_t^{US} = \alpha^{industry} + \beta_t^{industry} (IV_t^{industry}) + \varepsilon_t^{industry}$$

Where

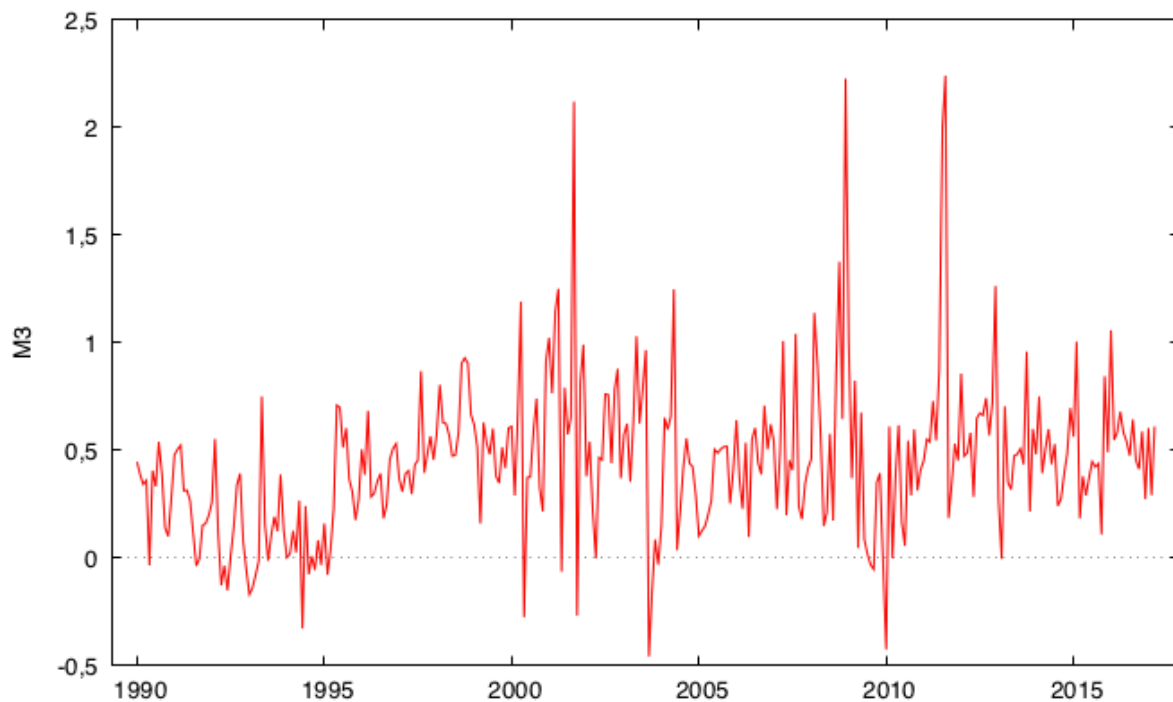
- IIP_t^{US} is the monthly U.S. IIP,
- $\alpha^{industry}$ is the monthly constant for each industry portfolio,
- $\beta_t^{industry}$ is the monthly coefficient for each industry portfolio,
- $IV_t^{industry}$ is the monthly idiosyncratic volatility for each industry portfolio, and
- $\varepsilon_t^{industry}$ refers to the monthly residuals for each industry portfolio.

The monthly U.S. industrial-production growth rate is regressed on the monthly idiosyncratic volatility of our industry portfolios' returns. We perform a student test where the null hypothesis is that $\beta_t^{industry} = 0$, and the alternative hypothesis is that $\beta_t^{industry} \neq 0$. If the observed p-value is lower than $\alpha\%$ ($\alpha = 1\%$, 5% or 10%), then we reject the null hypothesis

that $\beta_t^{industry} = 0$. This implies that we do not reject the alternative hypothesis that $\beta_t^{industry} \neq 0$. As a result, we can argue that there is a significant linear relationship between the monthly idiosyncratic volatility of our industry portfolios' returns and the monthly U.S. M3 growth rate at a level of significance of $\alpha\%$.

ii. The relationship between M3 and the idiosyncratic volatility of our industry portfolios

As for the GDP, we analyse the existence of any relationship between M3 and idiosyncratic volatility. We have the time series; therefore, before computing our regression, we again first verify graphically the stationarity of our variables and make all the required transformations, since they are necessary conditions for obtaining meaningful results. The following graph illustrating the evolution of this time series show us that it does not appear clearly that the time series is not stationary.



As a result, we directly regress the monthly M3 data, which is our dependent variable (LHS), on the monthly idiosyncratic volatility of our industry portfolios' returns, which is our independent variable. We obtain the following equation:

$$MS_t^{US} = \alpha^{industry} + \beta_t^{industry}(IV_t^{industry}) + \varepsilon_t^{industry}$$

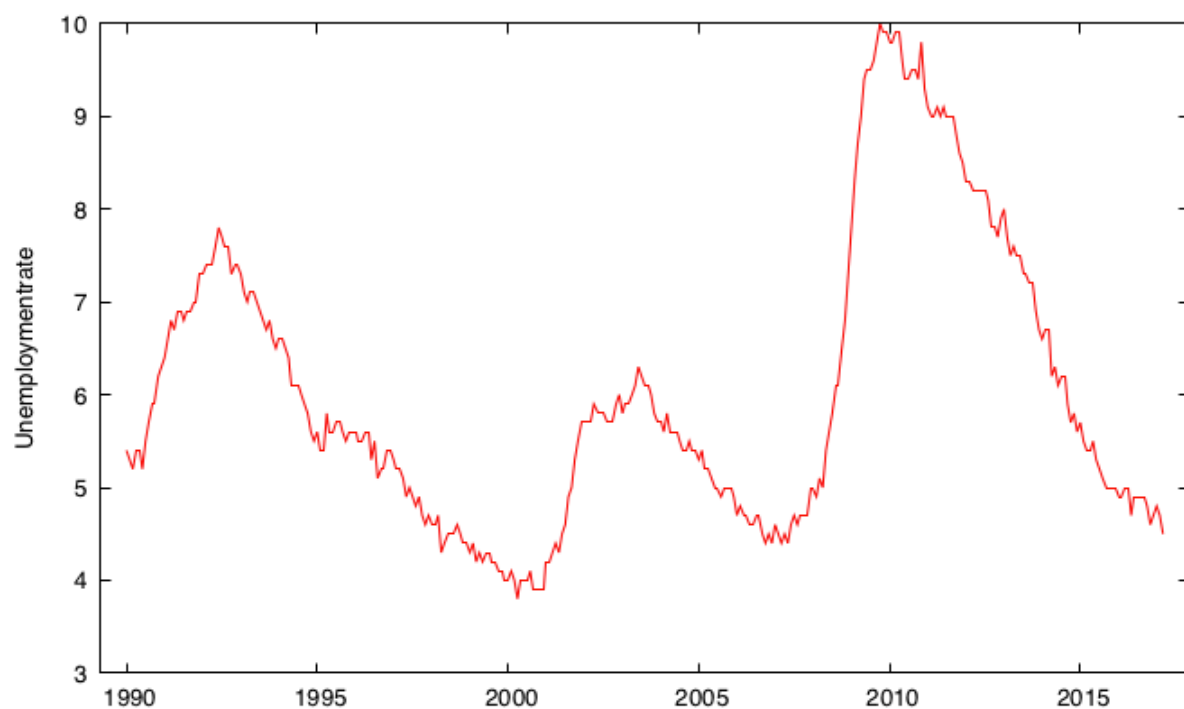
Where

- MS_t^{US} is the monthly U.S. M3 growth rate,
- $\alpha^{industry}$ is the monthly constant for each industry portfolio,
- $\beta_t^{industry}$ is the monthly coefficient for each industry portfolio,
- $IV_t^{industry}$ is the monthly idiosyncratic volatility for each industry portfolio, and
- $\varepsilon_t^{industry}$ represents the monthly residuals for each industry portfolio.

The monthly U.S. M3 growth rate is regressed on the monthly idiosyncratic volatility of our industry portfolios' returns. We perform a student test where the null hypothesis is that $\beta_t^{industry} = 0$, and the alternative hypothesis is that $\beta_t^{industry} \neq 0$. If the observed p-value is lower than $\alpha\%$ ($\alpha = 1\%, 5\%$ or 10%), then we reject the null hypothesis that $\beta_t^{industry} = 0$. This implies that we do not reject the alternative hypothesis that $\beta_t^{industry} \neq 0$. As a result, we can argue that there is a significant linear relationship between the monthly idiosyncratic volatility of our industry portfolios' returns and the monthly U.S. M3 growth rate at a level of significance of $\alpha\%$.

iii. The relationship between the unemployment rate and the idiosyncratic volatility of our industry portfolios

Finally, we perform the same analyse for our last variable, the unemployment rate. Since we have time series, before computing our regression, we first verify graphically the stationarity of our variables and make all the required transformations, since they are necessary conditions for obtaining meaningful results. Hereafter we can see that there is not any problem of stationarity.



As a result, we regress the monthly unemployment rate, which is our dependent variable, on the monthly idiosyncratic volatility of our industry portfolios' returns, which is our independent variable. We obtain the following equation:

$$UNP_t^{US} = \alpha^{industry} + \beta_t^{industry} (IV_t^{industry}) + \varepsilon_t^{industry}$$

Where

- UNP_t^{US} is the monthly U.S. unemployment rate,
- $\alpha^{industry}$ is the monthly constant for each industry portfolio,
- $\beta_t^{industry}$ is the monthly coefficient for each industry portfolio,
- $IV_t^{industry}$ is the monthly idiosyncratic volatility for each industry portfolio, and
- $\varepsilon_t^{industry}$ represents the monthly residuals for each industry portfolio.

The monthly U.S. unemployment rate is regressed on the monthly idiosyncratic volatility of our industry portfolios' returns. We perform a student test where the null hypothesis is that $\beta_t^{industry} = 0$, and the alternative hypothesis is that $\beta_t^{industry} \neq 0$. If the observed p-value is lower than $\alpha\%$ ($\alpha = 1\%$, 5% or 10%), then we reject the null hypothesis that $\beta_t^{industry} = 0$. This implies that we do not reject the alternative hypothesis that $\beta_t^{industry} \neq 0$. As a result, we can argue that there is a significant linear relationship between the monthly idiosyncratic volatility of our industry portfolios' returns and the monthly U.S. M3 unemployment rate at a level of significance of $\alpha\%$.

6) Empirical Results and Discussion

a) Idiosyncratic volatility

i) Descriptive statistics

1. Time-variation analysis

a. Introduction

The results of the analysis regarding idiosyncratic volatility in the U.S. market is organised as follows:

On the one hand, we examined the results to determine whether the formulated assumptions regarding the idiosyncratic-volatility behaviour of stock returns is maintained.

On the other hand, we investigated the idiosyncratic-volatility behaviour within different industries.

b. Assessing the hypotheses

i. Time intervals

Our first time-interval hypothesis regarding the time-variation behaviour of the idiosyncratic component of stock returns in the U.S. market is as follows:

⇒ H1.1. The idiosyncratic volatility of stock returns increased from the beginning of our period, which is January 1990, until the end of the 1990s.

From the figure 8 of the monthly idiosyncratic volatility, we can affirm that the idiosyncratic component of all 38 industry-portfolios' stock returns increased, on average, in the U.S. market from January 1990 to the end of the 1990's.

The first time-interval assumption is then accepted.

Our second time-interval hypothesis regarding the time-variation behaviour of the idiosyncratic component of stock returns in the U.S. market is as follows:

⇒ **H1.2. The idiosyncratic volatility of stock returns increased between January 2001 and the end of 2008.**

From the figure 9, of the monthly idiosyncratic volatility, we can affirm that the idiosyncratic component of stock returns of all 38 industry-portfolios' stock returns decreased slightly, on average, in the U.S. market between January 2001 and the end of 2008.

The second time-interval assumption is thus rejected.

Our third time-interval hypothesis regarding the time-variation behaviour of the idiosyncratic component of stock returns in the U.S. market is as follows:

⇒ **H1.3. The idiosyncratic volatility of stock returns increased between January 2009 and March 2017.**

From the figure 10 of the monthly idiosyncratic volatility, we can affirm that the idiosyncratic component of stock returns of all 38 industry-portfolios' stock returns decreased slightly, on average, in the U.S. market between January 2009 and March 2017.

The third time-interval assumption is thus rejected.

ii. Significant events

The first significant-event hypothesis regarding the time-variation behaviour of the idiosyncratic component of stock returns in the U.S. market is as follows:

⇒ H2.1.: The idiosyncratic volatility of stock returns strongly increased during the Internet bubble, which occurred in the second part of the 1990s until January 2000.

This rise of stock return's idiosyncratic volatility is apparent in all of the industry portfolios. The figure 8 regarding the evolution of idiosyncratic volatility from 1990-2017 illustrates this trend.

Therefore, the first significant-event assumption is accepted.

⇒ H2.1.1. The volatility shock is more significant in the tertiary sector.

This rise of stock return's idiosyncratic volatility is apparent in all of the industry portfolios.

The figure 3 compares the evolution of idiosyncratic volatility between the different sectors from 1990 to 2017.

Based on that, during the Internet bubble, we observe a more significant shock in the tertiary sector than others.

In fact, during the Internet bubble at the end of the 90's, the tertiary sector, such as transportation, electric, gas and sanitary services, wholesale trade and retail trade strongly increased in term of idiosyncratic volatility.

- In the primary sector (figure 4), the idiosyncratic component of stock returns increased from approximately 5 during the 1990s to 10 in January 2000

- In the secondary sector (figure 5), the idiosyncratic component of stock returns increased from approximately 3 during the 1990s to 10 in January 2000
- In the tertiary sector (figure 6), the idiosyncratic component of stock returns increased from approximately 3 during the 1990s to 28 in January 2000
- In the quaternary sector (figure 7), the idiosyncratic component of stock returns increased from approximately 4 during the 1990s to 15 in January 2000

As we can see on the tertiary sector (figure 6), the drop in the idiosyncratic volatility is much greater than in other sectors during this time period.

Therefore, our assumption is accepted.

⇒ **H2.2. The idiosyncratic volatility of stock returns strongly increased during the subprime crisis from the beginning of 2007 until October 2008.**

This rise of stock return's idiosyncratic volatility is apparent in all of the industry portfolios.

The figure 9 depicting the evolution of idiosyncratic volatility from 2001-2008 illustrates this trend.

Therefore, the second significant-event assumption is accepted.

⇒ **H2.2.1. The volatility shock increased significantly in the financial sector.**

During the subprime crisis, idiosyncratic volatility strongly increased in the financial sector.

In the financial sector (figure 44), the idiosyncratic component of stock returns increased from 2.86 in the end of 2007 to 7.74 in the end of 2008.

As a result, we accept the hypothesis arguing that the shock was significant in the financial sector.

⇒ **H2.3. The idiosyncratic volatility of stock returns increased during the Sovereign Debt crisis, which occurred from October 2010 until July 2011.**

This decrease of stock return's idiosyncratic volatility is apparent in all of the industry portfolios.

The figure 10 depicting the evolution of idiosyncratic volatility from 2009-2017 illustrates this trend.

Therefore, the third significant-event assumption is rejected.

⇒ **H2.3.1. The volatility shock increased significantly in the public sector.**

During the subprime crisis, idiosyncratic volatility strongly increased in the public sector.

In the financial sector (figure 46), the idiosyncratic component of stock returns increased from 2.65 in the end of 2007 to 13.69 in the beginning of 2009.

As a result, we accept the hypothesis arguing that the shock was significant in the public sector.

c. Additional observations

Besides these general trends in idiosyncratic volatility, we observe a rapid increase in the idiosyncratic volatility of the stock returns of a significant number of industry portfolios.

In particular, the industries which display the greatest peaks in idiosyncratic volatility around this time are the following: Food Products, Beer and Liquor, Recreation, Healthcare,

Medical Equipment, Construction, Shipbuilding and Railroad Equipment, Utilities, Business Services, Computer Software, Electronic equipments, and Business Supplies.

ii) Conclusion

1. Empirical results summary

The analysis of the results concerning the idiosyncratic component of stock returns led to the validation of 6 out of our 9 hypotheses.

As a conclusion, we can describe the behaviour of the idiosyncratic volatility of stock returns over our sample period. The following behaviour can be observed, thanks to the figure 1 representing the average of the 38 portfolios:

- 1) A slight increase from the beginning of 1990 to 1991.
- 2) A continuous decrease from 1991 to the end of the first half of the 1990s.
- 3) A continuous increase from January 1995 to the end of the 1990s, with a strong increase between 1998 and 2000.
- 4) A peak around the second half of 2000.
- 5) A more modest peak in July 2002, and a continuous decrease until around July of 2007.
- 6) A second surge, starting in July 2007, which peaked in September 2008, followed by a decrease.
- 7) A rather stable behaviour from 2010 onwards to the end of the period in March 2017

We can thus state that there were two strong surges in the idiosyncratic volatility of the industry portfolios' stock returns in the period starting in January 1990 and ending in March 2017. The first surge occurred in 2000, around April, and coincides with the stock-market crash caused mainly due to the speculative Internet bubble. The second surge occurred in 2008, around September, and coincides with the bankruptcy of Lehman Brothers in the wake of the 2008 subprime crisis.

b) Macroeconomic variables

i) Relationship between idiosyncratic volatility and the selected macroeconomic variables

1. *The relationship between the industrial production index (as a proxy for GDP) and the idiosyncratic volatility of our industry portfolios*

We regressed the monthly U.S. IIP, which is our dependent variable (LHS), on the monthly idiosyncratic volatility of our industry portfolios' returns, which is our independent variable.

We obtain the linear regression as follows:

$$IP_t^{US} = \alpha^{industry} + \beta_t^{industry} (IV_t^{industry}) + \varepsilon_t^{industry}$$

Where

- IP_t^{US} is the monthly U.S. IIP,
- $\alpha^{industry}$ is the monthly constant for each industry portfolio,
- $\beta_t^{industry}$ is the monthly coefficient for each industry portfolio,
- $IV_t^{industry}$ is the monthly idiosyncratic volatility for each industry portfolio, and
- $\varepsilon_t^{industry}$ represents the monthly residuals for each industry portfolio.

We performed a student test where the null hypothesis is that $\beta_t^{industry} = 0$, and the alternative hypothesis is that $\beta_t^{industry} \neq 0$. If the observed p-value is lower than $\alpha\%$ ($\alpha = 1\%, 5\%$ or 10%), then we reject the null hypothesis that $\beta_t^{industry} = 0$, and we do not reject the alternative hypothesis that $\beta_t^{industry} \neq 0$. The results of our regression are available in table 1 in the appendix; which contains the coefficient $\beta_t^{industry}$, the p-value and the level of significance. Based on that, we can make the following observation:

We can see that there is a significant negative linear relationship between the monthly U.S. IIP portfolio and the returns of 32 of our 38 industry portfolios.

Regarding the level of significance, we can make the following observations at these levels of significance:

- At 1%, there is a negative linear relationship between the monthly U.S. IIP and the monthly idiosyncratic volatility of the portfolio returns for the following variables (representing our different industries): agriculture, mining, oil and gas extraction, non-metallic minerals except fuels, construction, food, textile mill products, apparel and other textile products, lumber and wood products, furniture and fixtures, paper and allied products, printing and publishing, petroleum, rubber, leather, glass products, metal, electrical and electronic equipment, transportation equipment, instruments, transportation, telephone, electric, gas and water supply, wholesale, retail stores, finance, insurance and real estate, services and other.
- At 5%, there is a negative linear relationship between the monthly U.S. IIP and the monthly idiosyncratic volatility of the portfolio returns for the following variables (representing our different industries): chemicals, machinery and manufacturing.
- At 10%, there is a negative linear relationship between the monthly U.S. IIP and the monthly idiosyncratic-volatility variable of the radio and television broadcasting (TV) portfolio returns.

Based on the above, we can now assess whether our hypotheses will be rejected or not.

Our first hypothesis regarding the relationship that may exist between the idiosyncratic volatility of our industry portfolios and the IIP (acting as a proxy for GDP) was as follows:

- ⇒ The idiosyncratic component of stock returns is positively related to the industrial production index. Based on our results, we reject this hypothesis.

2. The relationship between the monthly M3 money supply and the idiosyncratic volatility of our industry portfolios

We regressed the monthly M3 money supply, which is our dependent variable (LHS), on the monthly idiosyncratic volatility of our industry portfolios' returns, which is our independent variable.

We obtain the following linear regression:

$$M3_t^{US} = \alpha^{industry} + \beta_t^{industry}(IV_t^{industry}) + \varepsilon_t^{industry}$$

Where

- $M3_t^{US}$ is the monthly U.S. M3 growth rate,
- $\alpha^{industry}$ is the monthly constant for each industry portfolio,
- $\beta_t^{industry}$ is the monthly coefficient for each industry portfolio,
- $IV_t^{industry}$ is the monthly idiosyncratic volatility for each industry portfolio, and
- $\varepsilon_t^{industry}$ represents the monthly residuals for each industry portfolio,

We performed a student test where the null hypothesis is that $\beta_t^{industry} = 0$, and the alternative hypothesis is that $\beta_t^{industry} \neq 0$. If the observed p-value is lower than $\alpha\%$ ($\alpha = 1\%, 5\%$ or 10%), then we reject the null hypothesis that $\beta_t^{industry} = 0$, and we do not reject the alternative hypothesis that $\beta_t^{industry} \neq 0$. The results of our regression are available in table 2 in the appendix; this table contains the coefficient $\beta_t^{industry}$, the p-value and the level of significance.

We observe that there is a significant positive linear relationship between the monthly M3 data and the returns of 35 of our 38 industry portfolios, while there is a significant negative linear relationship between the monthly M3 data and 1 of our 38 industry portfolios' returns.

Regarding the level of significance, we can make the following observations at these levels of significance:

- At 1%, there is a positive linear relationship between the monthly U.S. M3 data and the monthly idiosyncratic volatility of the portfolio returns for the following variables (representing our different industries): agriculture, mining, oil, non-metallic minerals (stone), construction, food, textile mill products, apparel, lumber and wood products, furniture and fixtures (chair), paper, printing and publishing, chemicals, petroleum, rubber, leather, glass, primary metal industries, fabricated metal products, machinery, electrical and electronic equipment, transportation equipment, instruments, manufacturing, transportation, telephone, radio and television broadcasting (TV), electric, gas and water supply (utils), wholesale, retail stores, finance, insurance and real estate (money), services, public administration and other.
- At 5%, there is a positive linear relationship between the monthly U.S. M3 data and the monthly idiosyncratic volatility of the smoke portfolio's returns.
- At 5%, there is a negative linear relationship between the monthly U.S. M3 data and the monthly idiosyncratic volatility of the steam portfolio's returns.

Our hypothesis concerning the relationship that may exist between the idiosyncratic volatility of our industry portfolios and the M3 money supply stated the following:

- ⇒ The idiosyncratic component of stock returns is positively related to money supply (M3). Based on our results, we do not reject this hypothesis.

3. *The relationship between the unemployment rate and the idiosyncratic volatility of our industry portfolios*

We regressed the monthly U.S. unemployment rate, which is our dependent variable (LHS), on the monthly idiosyncratic volatility of our industry portfolios' returns, which is our independent variable.

We obtain the linear regression as follows:

$$UNP_t^{US} = \alpha^{industry} + \beta_t^{industry} (IV_t^{industry}) + \varepsilon_t^{industry}$$

Where

- UNP_t^{US} is the monthly U.S. unemployment rate,
- $\alpha^{industry}$ is the monthly constant for each industry portfolio,
- $\beta_t^{industry}$ is the monthly coefficient for each industry portfolio,
- $IV_t^{industry}$ is the monthly idiosyncratic volatility for each industry portfolio, and
- $\varepsilon_t^{industry}$ represents the monthly residuals for each industry portfolio.

We performed a student test where the null hypothesis is that $\beta_t^{industry} = 0$, and the alternative hypothesis is that $\beta_t^{industry} \neq 0$. If the observed p-value is lower than $\alpha\%$ ($\alpha = 1\%, 5\%$ or 10%), then we reject the null hypothesis that $\beta_t^{industry} = 0$, and we do not reject the alternative hypothesis that $\beta_t^{industry} \neq 0$. The results of our regression are available in table 3 in the appendix; the table contains the coefficient $\beta_t^{industry}$, the p-value and the level of significance.

We can see that there is a significant negative linear relationship between the monthly U.S. unemployment rate and the returns of 27 of our 38 industry portfolios, while there is a significant positive linear relationship between the monthly U.S. unemployment rate and 3 of our 38 industry portfolios' returns.

Regarding the level of significance, we can make the following observations at these levels of significance:

- At 1%, there is a negative linear relationship between the monthly U.S. unemployment rate and the monthly idiosyncratic volatility of the portfolio returns for the following variables (representing our different industries): mining, oil, food, tobacco products (smoke), paper, chemicals, petroleum, primary metal industries, fabricated metal products, machinery, electrical and electronic equipment, instruments, manufacturing, transportation, telephone, radio and television broadcasting (TV), electric, gas, and water supply (utils), sanitary services (garbg), wholesale, retail stores, services, public administration (gov) and other.
- At 5%, there is a negative linear relationship between the monthly U.S. unemployment rate and the monthly idiosyncratic volatility of the portfolio returns for the following variables (representing our different industries): construction and finance, insurance, and real estate (money).
- At 5%, there is a positive linear relationship between the monthly U.S. unemployment rate and the monthly idiosyncratic volatility of the portfolio returns for the following variables (representing our different industries): chair and glass.
- At 10%, there is a negative linear relationship between the monthly U.S. unemployment rate and the monthly idiosyncratic volatility variable of the transportation equipment (cars) portfolio's returns.
- At 10%, there is a positive linear relationship between the monthly U.S. unemployment rate and the monthly idiosyncratic volatility variable of the textile mill products portfolio's returns.

Based on the above, we can now assess whether our hypotheses will be rejected or not.

Our first hypothesis regarding the relationship that may exist between the idiosyncratic volatility of our industry portfolios and the unemployment rate was as follows:

⇒ The idiosyncratic component of stock returns is negatively related to the unemployment rate. Based on our results, we do not reject this hypothesis.

7) Conclusion

Throughout this thesis, we had the opportunity to investigate the idiosyncratic volatility of stock returns for the period 1990-2017 and the relationship that may exist between the idiosyncratic risk and the selected macroeconomic variables such as unemployment rates, money supply and the index of industrial production.

On one hand, at the beginning of this study we made some hypotheses that we tested right after practicing the methodology to compute the idiosyncratic component of stock returns and the possible link between this firm-specific risk and the unemployment rates, the index of industrial production and the M3 money supply. On the other hand, thanks to statistical descriptions, we were able to accept or reject hypotheses that we made. Which bring us to validate 8 out of 12 hypotheses specified.

Firstly, concerning the idiosyncratic volatility behaviour, we observe a slight increase from the beginning of 1990 to 1991. Followed by a continuous decrease from 1991 to the end of the first half of the 1990s. To continue, an increase from January 1995 to the end of the 1990s, with a strong increase between 1998 and 2000. On the one hand, it is important to note the first peak on the figure 1 that appeared in 2000. Some years after, the emergence of a modest peak in July 2002, and a continuous decrease until around July of 2007. On the other hand, the occurrence of a second surge, starting in July 2007, which peaked in September 2008, due to the subprime crisis that overwhelmed the United States. Furthermore, the idiosyncratic volatility remained stable on average from 2010 onwards to the end of the period in March 2017.

Second of all, regarding the possible relationship between U.S. macroeconomic variables and the idiosyncratic component of stock returns. We found out a negative relationship between the idiosyncratic volatility and the index of industrial production. In the same, the relation between the unemployment rates and the idiosyncratic volatility can be assessed on average as negative. Finally, we documented a positive relationship between the idiosyncratic volatility and the M3 money supply.

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9) Appendix

Table 1. variables description

Number	Variables	Content
1	Agric	Agriculture, forestry, and fishing 0100-0999
2	Mines	Mining 1000-1299
3	Oil	Oil and Gas Extraction 1300-1399
4	Stone	Nonmetallic Minerals Except Fuels 1400-1499
5	Cnstr	Construction 1500-1799
6	Food	Food and Kindred Products 2000-2099
7	Smoke	Tobacco Products 2100-2199

8	Txtls	Textile Mill Products 2200-2299
9	Apprl	Apparel and other Textile Products 2300-2399
10	Wood	Lumber and Wood Products 2400-2499
11	Chair	Furniture and Fixtures 2500-2599
12	Paper	Paper and Allied Products 2600-2661
13	Print	Printing and Publishing 2700-2799
14	Chems	Chemicals and Allied Products 2800-2899
15	Ptrlm	Pertroleum and Coal Products

		2900-2999
16	Rubbr	Rubber and Miscellaneous Plastics Products 3000-3099
17	Lethr	Leather and Leather Products 3100-3199
18	Glass	Stone, Clay nad Glass Products 3200-3299
19	Metal	Primary Metal Industries 3300-3399
20	MtIPr	Fabricated Metal Products 3400-3499
21	Machn	Machinery, Except Electrical 3500-3599
22	Electr	Electrical and Electronic Equipment 3600-3699
23	Cars	Transportation Equipment

		3700-3799
24	Instr	Instruments and Related Products 3800-3879
25	Manuf	Miscellaneous Manufacturing Industries 3900-3999
26	Trans	Transportation 4000-4799
27	Phone	Telephone and Telegraph Communication 4800-4829
28	TV	Radio and Television Broadcasting 4830-4899
29	Utils	Electric, Gas, and Water Supply 4900-4949
30	Garbg	Sanitary Services

		4950-4959
31	Steam	Steam Supply 4960-4969
32	Water	Irrigation Systems 4970-4979
33	Whlsl	Wholesale 5000-5199
34	Rtail	Retail Stores 5200-5999
35	Money	Finance, Insurance, and Real Estate 6000-6999
36	Srvc	Services 7000-8999
37	Govt	Public Administration 9000-9999
38	Other	Almost Nothing

Source : http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 2. Ordinary least squares results for the linear regression on the IIP

$$IIP_t^{US} = \alpha^{industry} + \beta_t^{industry}(IV_t^{industry}) + \varepsilon_t^{industry}$$

Variables	Coefficient	P-Value	Level of significance
Agric	-0,0598671	1,97E-08	***
Mines	-0,058144	5,45E-11	***
Oil	-0,0573924	1,02E-09	***
Stone	-0,0729764	2,06E-06	***
Cnstr	-0,0794784	2,22E-07	***
Food	-0,0600566	0,0046	***
Smoke	-0,0067616	0,4979	
Txtls	-0,0755384	4,73E-08	***
Appr	-0,100926	5,63E-08	***
Wood	-0,0429654	0,0083	***
Chair	-0,107153	1,02E-08	***
Paper	-0,0484085	0,0086	***
Print	-0,0648832	0,0005	***
Chems	-0,0485499	0,0249	**
Ptrlm	-0,0519867	0,0003	***
Rubbr	-0,0952599	1,11E-05	***
Lethr	-0,0670951	5,09E-06	***
Glass	-0,0668527	0,0003	***
Metal	-0,0892119	1,54E-12	***
MtlPr	-0,0107797	0,5421	
Machn	-0,0441705	0,0214	**
Elctr	-0,0459552	0,0035	***
Cars	-0,129488	3,15E-07	***
Instr	-0,123454	0,0001	***

Manuf	-0,0407363	0,0343	**
Trans	-0,136661	1,16E-09	***
Phone	-0,0658999	0,003	***
TVRF	-0,034899	0,0665	*
Utils	-0,0741926	2,79E-05	***
Garbg	0,000788759	0,9414	
Steam	0,000611241	0,6914	
Whlsl	-0,0722284	0,0039	***
Retail	-0,085576	1,08E-05	***
Money	-0,120377	5,14E-06	***
Srvc	-0,12643	8,79E-05	***
Gov	0,00630237	0,1044	
Other	-0,0607108	0,0017	***

Where

*** = 1%

** = 5%

* = 10%

Table 3. Ordinary least squares results for the linear regression on M3

$$M3_t^{US} = \alpha^{industry} + \beta_t^{industry}(IV_t^{industry}) + \varepsilon_t^{industry}$$

Variables	Coefficient	P-Value	Level of significance
Agric	0,0269	4,82E-05	***
Mines	0,0229	3,63E-05	***
Oil	0,0392	6,56E-12	***
Stone	0,0342	3,00E-04	***
Cnstr	0,0396	2,88E-05	***
Food	0,0501	1,00E-04	***
Smoke	0,0153	1,22E-02	**
Txtls	0,0446	1,48E-07	***
Appr	0,0525	4,70E-06	***
Wood	0,0265	7,80E-03	***
Chair	0,0457	8,37E-05	***
Paper	0,0379	7,00E-04	***
Print	0,0432	2,00E-04	***
Chems	0,0453	6,00E-04	***
Ptrlm	0,0484	3,07E-08	***
Rubbr	0,0680	2,64E-07	***
Lethr	0,0397	9,36E-06	***
Glass	0,0419	2,00E-04	***
Metal	0,0350	9,79E-06	***
MtlPr	0,0434	5,14E-05	***
Machn	0,0509	1,25E-05	***
Elctr	0,0459	1,54E-06	***
Cars	0,0672	1,67E-05	***
Instr	0,0943	1,09E-06	***
Manuf	0,0351	2,80E-03	***

Trans	0,0696	5,37E-07	***
Phone	0,0623	1,07E-08	***
TVRF	0,0314	6,90E-03	***
Utils	0,0746	1,81E-12	***
Garbg	0,0030	6,52E-01	
Steam	-0,0021	2,42E-02	**
Whlsl	0,0653	1,77E-05	***
Retail	0,0454	1,00E-04	***
Money	0,0675	3,21E-05	***
Srvc	0,0963	9,36E-07	***
Gov	-0,0006	7,93E-01	
Other	0,0592	4,82E-07	***

Where

*** = 1%

** = 5%

* = 10%

Table 4. Ordinary least squares results for the linear regression on UNP

$$UNP_t^{US} = \alpha^{industry} + \beta_t^{industry}(IV_t^{industry}) + \varepsilon_t^{industry}$$

Variables	Coefficient	P-Value	Level of significance
Agric	0,0429056	0,1405	
Mines	-0,0838603	0,0005	***
Oil	-0,156946	3,50E-10	***
Stone	-0,0740778	0,0753	*
Cnstr	-0,104649	0,0118	**
Food	-0,260466	3,28E-06	***
Smoke	-0,170025	4,21E-11	***
Txtls	0,0682046	7,02E-02	*
Appr	-0,0149429	7,68E-01	
Wood	0,044882	3,04E-01	
Chair	0,120796	1,79E-02	**
Paper	-0,280769	5,53E-09	***
Print	0,0164677	7,43E-01	
Chems	-0,379446	1,25E-11	***
Ptrlm	-0,265312	1,46E-12	***
Rubbr	-0,062578	2,86E-01	
Lethr	-0,0234158	5,55E-01	
Glass	0,109874	2,60E-02	**
Metal	-0,0949573	6,40E-03	***
MtlPr	-0,250894	5,52E-08	***
Machn	-0,238509	2,43E-06	***
Elctr	-0,191798	4,09E-06	***
Cars	-0,113248	9,99E-02	*
Instr	-0,282964	9,00E-04	***
Manuf	-0,215016	2,36E-05	***
Trans	-0,194776	1,50E-03	***

Phone	-0,187355	9,62E-05	***
TVRF	-0,195455	1,00E-04	***
Utils	-0,19753	2,91E-05	***
Garbg	-0,144087	2,94E-07	***
Steam	0,00130161	7,52E-01	
Whlsl	-0,303818	4,36E-06	***
Retail	-0,288578	2,01E-08	***
Money	-0,170553	1,68E-02	**
Srvc	-0,436604	3,13E-07	***
Gov	-0,0557717	3,90E-08	***
Other	-0,290341	1,17E-08	***

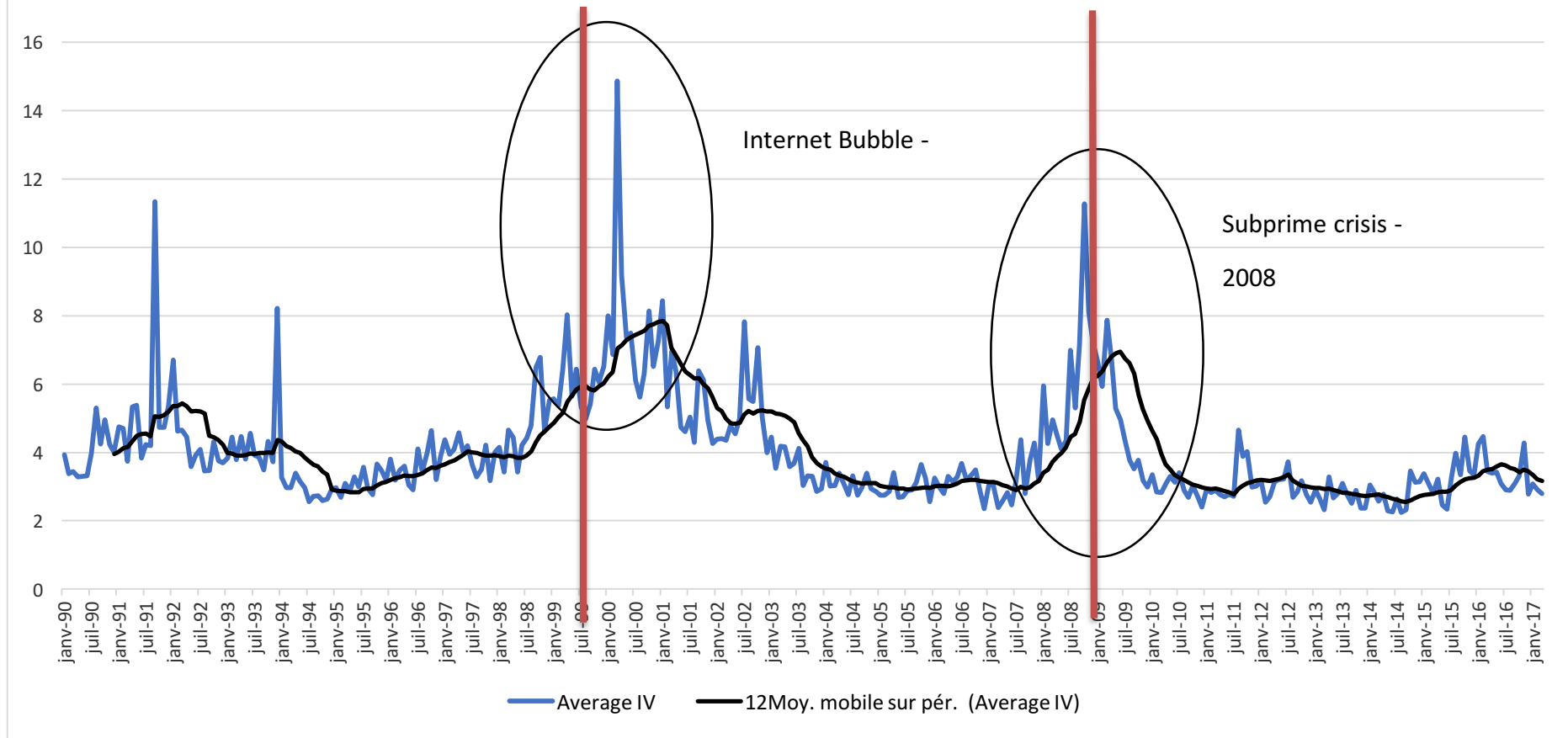
Where

*** = 1%

** = 5%

* = 10%

Figure 1 - Monthly idiosyncratic volatility for the 38 portfolios from 1990 to 2017



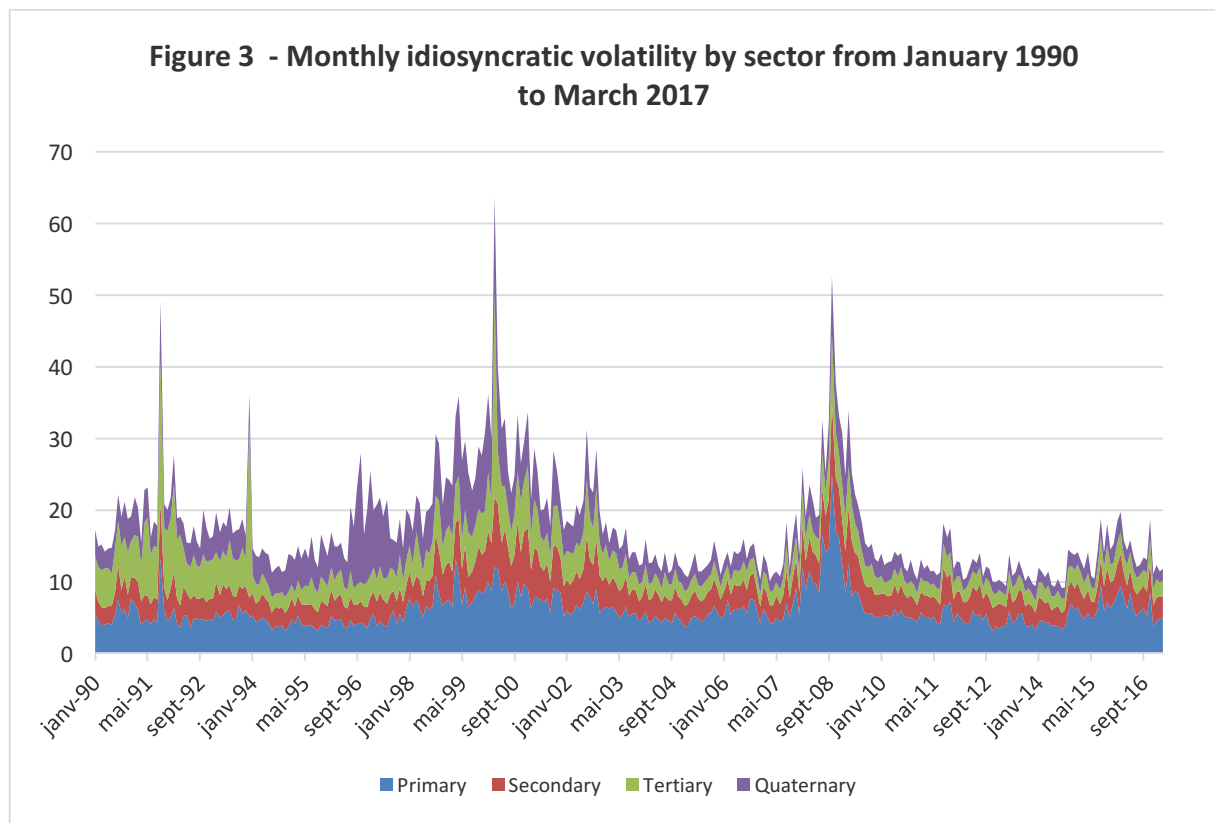
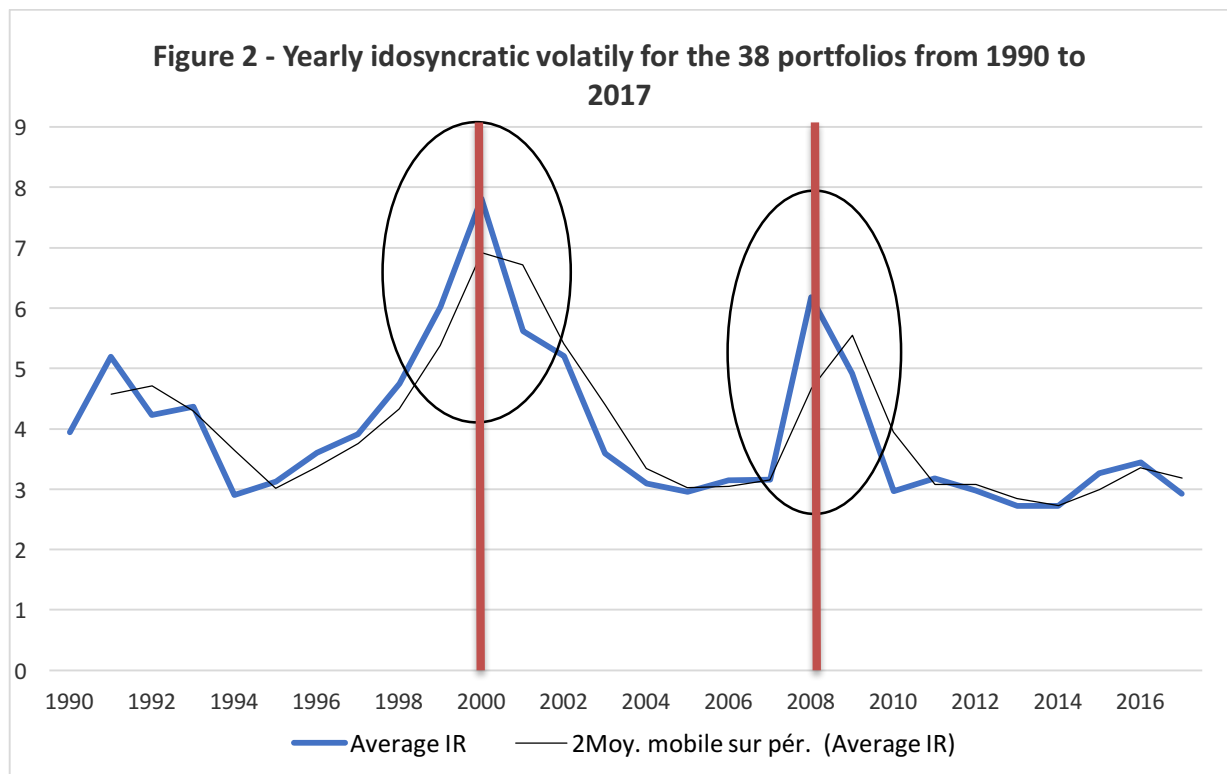


Figure 4 - Average idiosyncratic volatility for the primary sector from January 1990 to March 2017

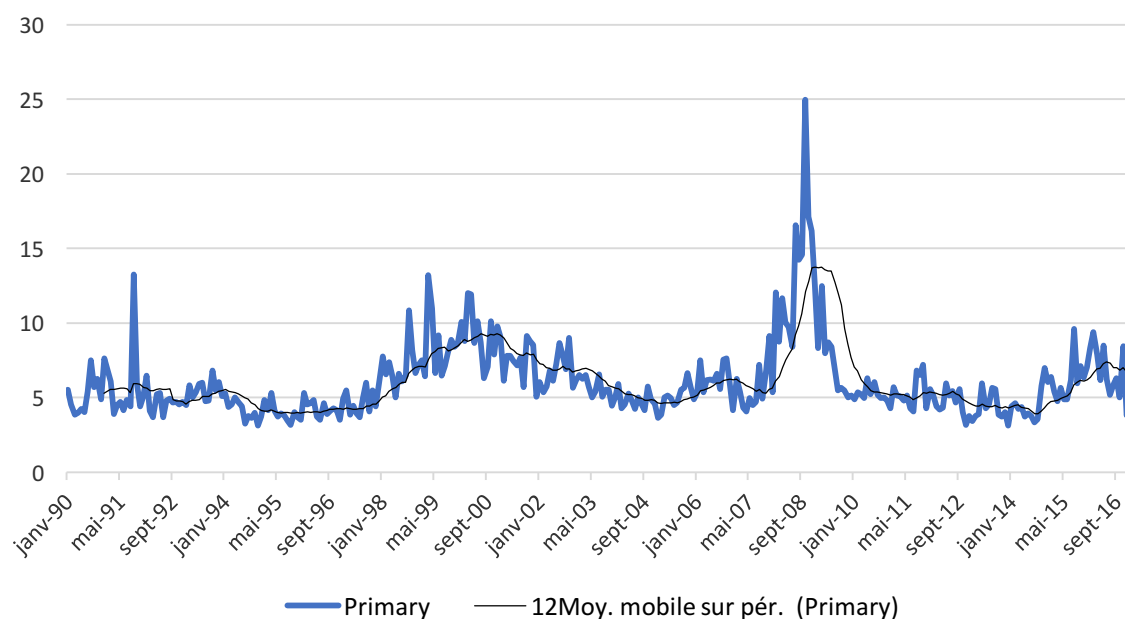


Figure 5 - Average idiosyncratic volatility for the secondary sector from January 1990 to March 2017

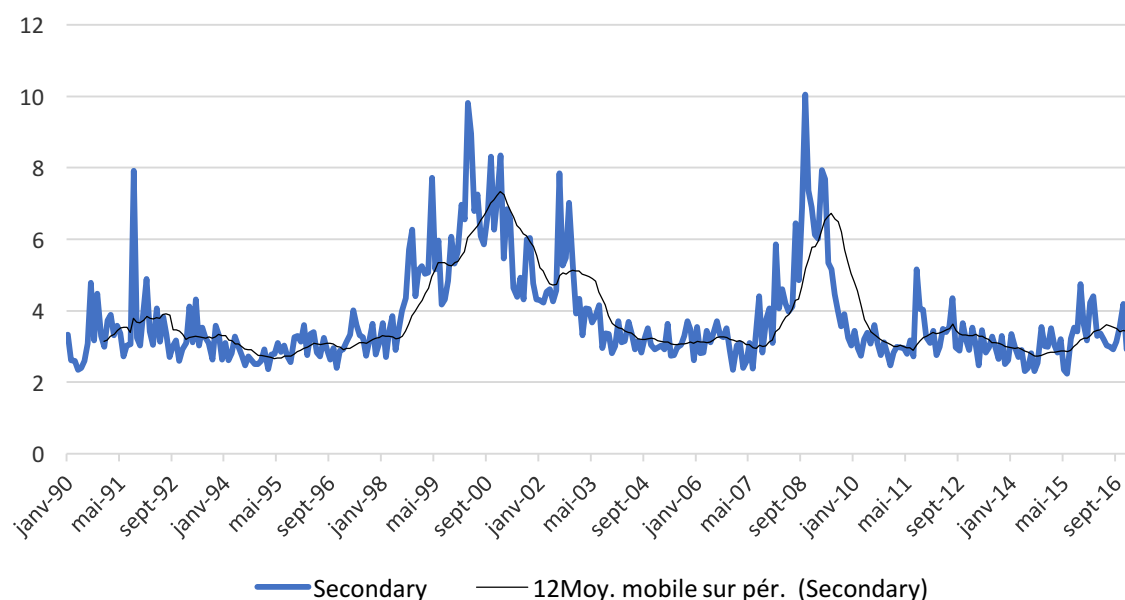


Figure 6 - Average idiosyncratic volatility for the tertiary sector from January 1990 to March 2017

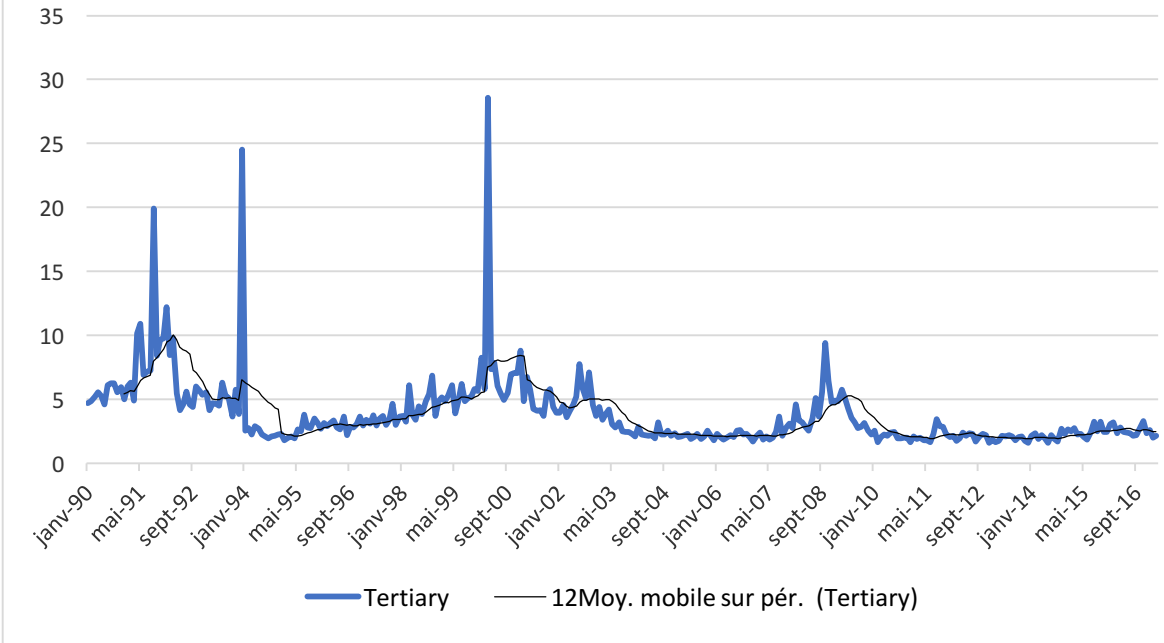


Figure 7 - Average idiosyncratic volatility for the quaternary sector from January 1990 to March 2017

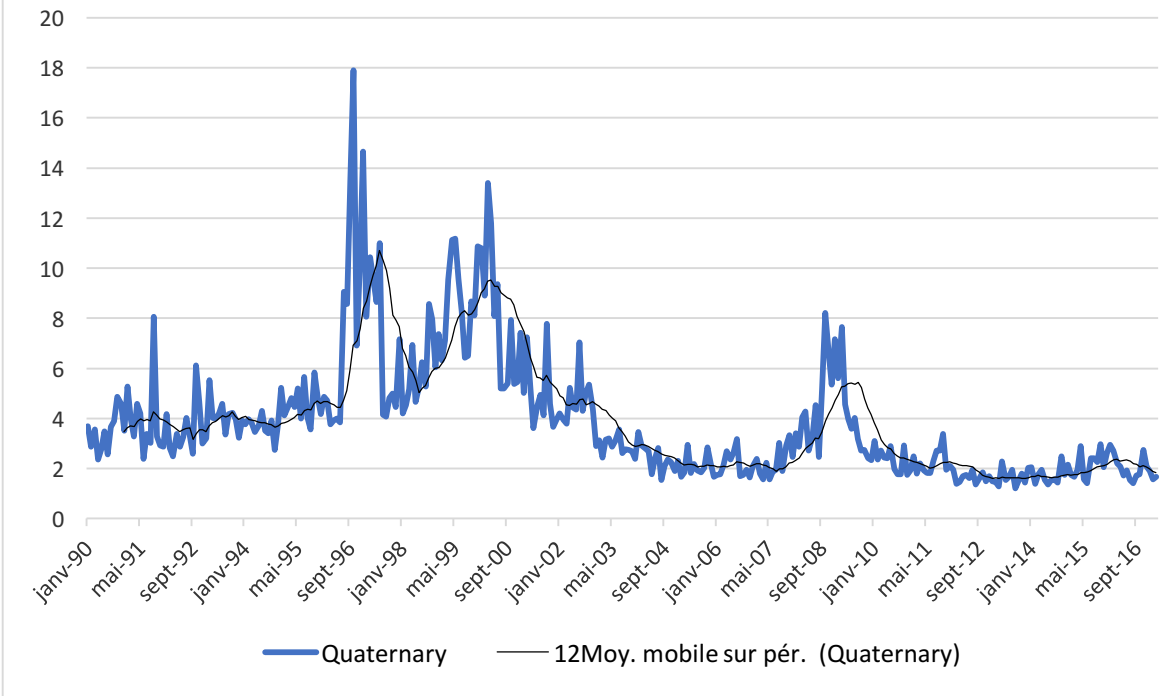


Figure 8 - Monthly average idiosyncratic volatility for the 38 industry portfolios from January 1990 to December 2000

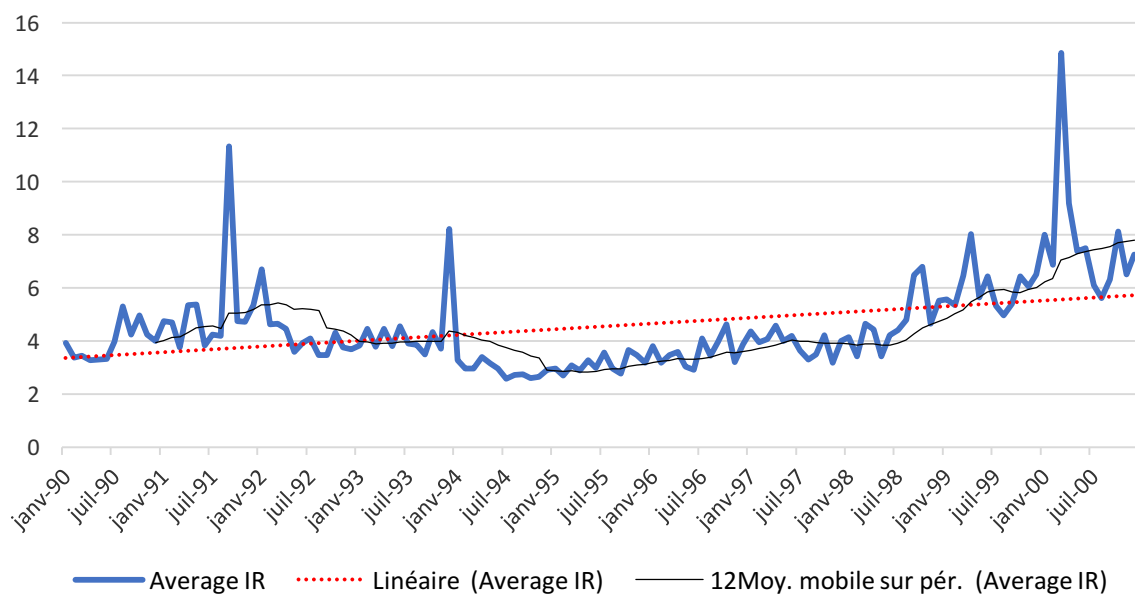


Figure 9 - Monthly average idiosyncratic volatility for the 38 industry portfolios from January 2001 to December 2008

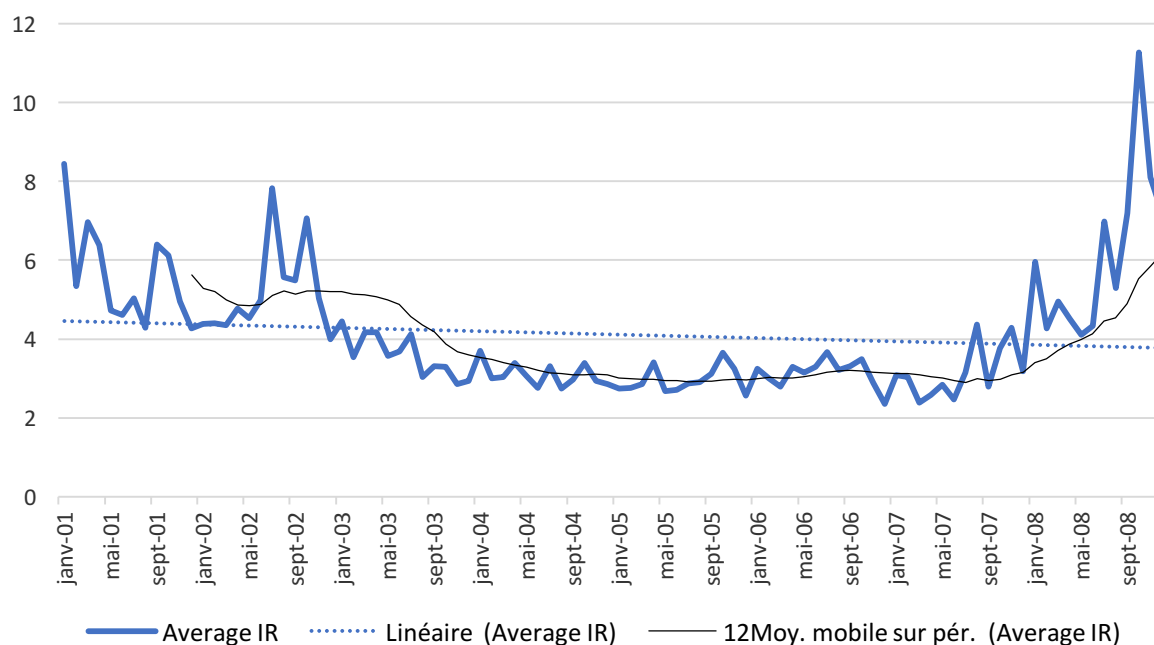


Figure 10 - Monthly average idiosyncratic volatility for the 38 industry portfolios from January 2009 to March 2017

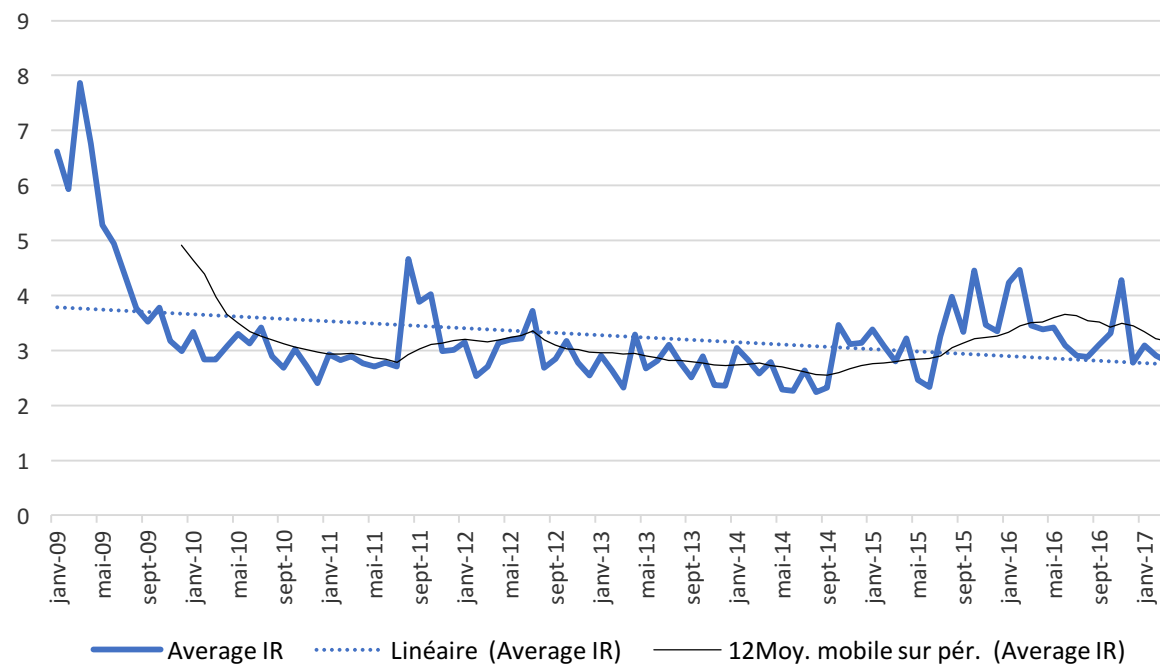


Figure 11 - Monthly idiosyncratic volatility of Agric from 01/1990 to 03/2017

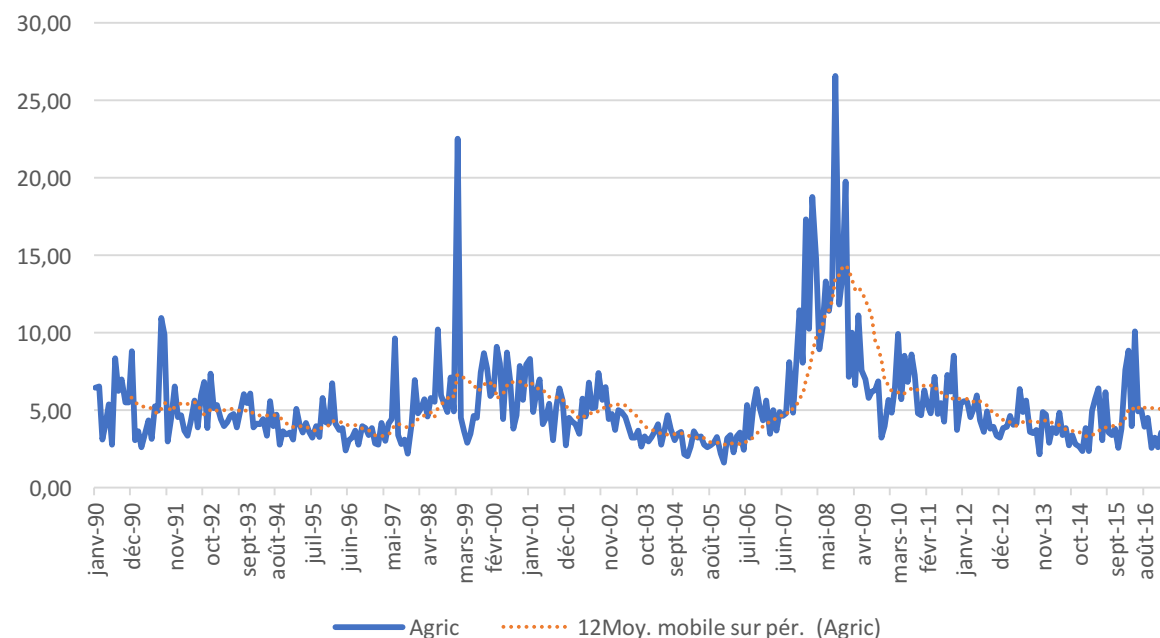


Figure 12 - Monthly idiosyncratic volatility of mines from 01/1990 to 03/2017

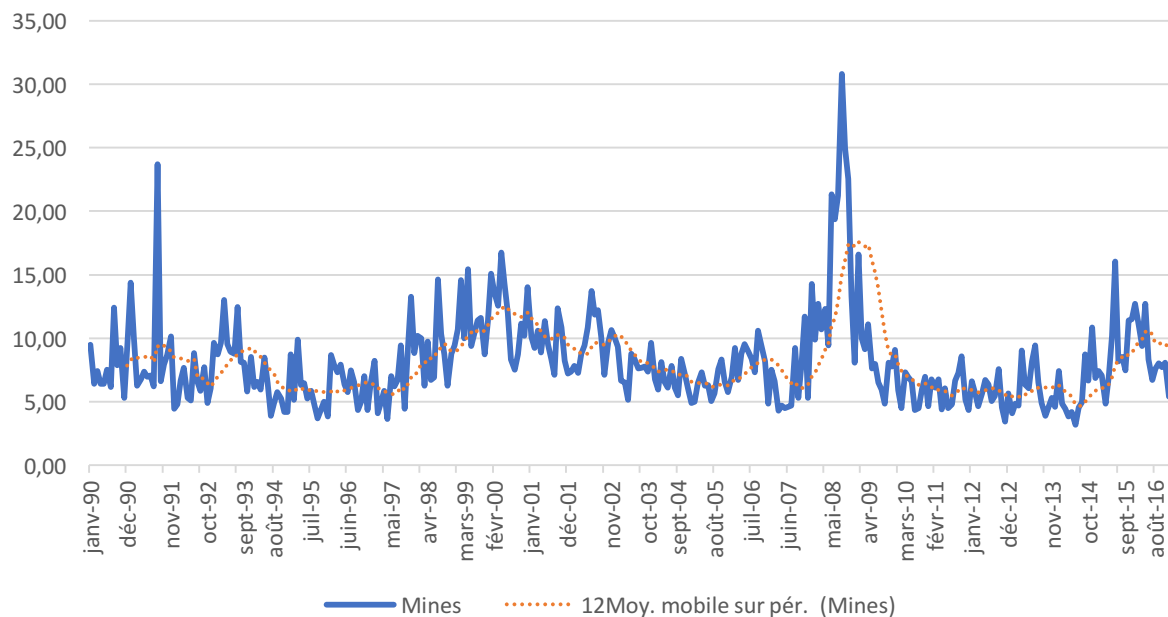


Figure 13 - Monthly idiosyncratic volatility of oil from 01/1990 to 03/2017

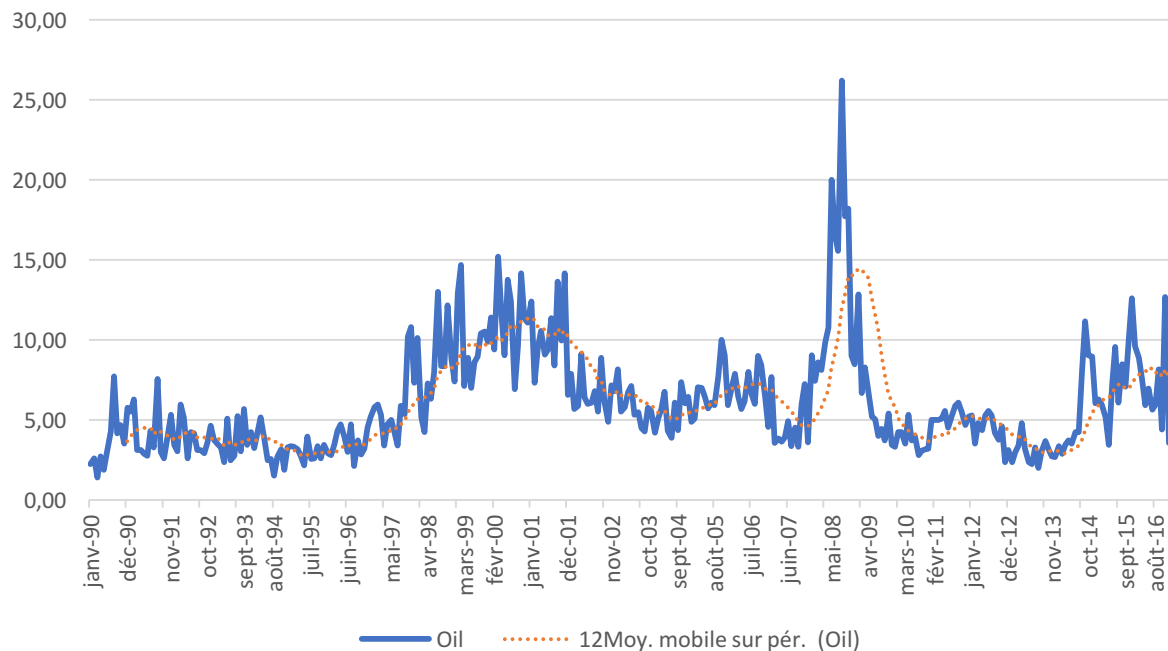


Figure 14 - Monthly idiosyncratic volatility of stone from 01/1990 to 03/2017

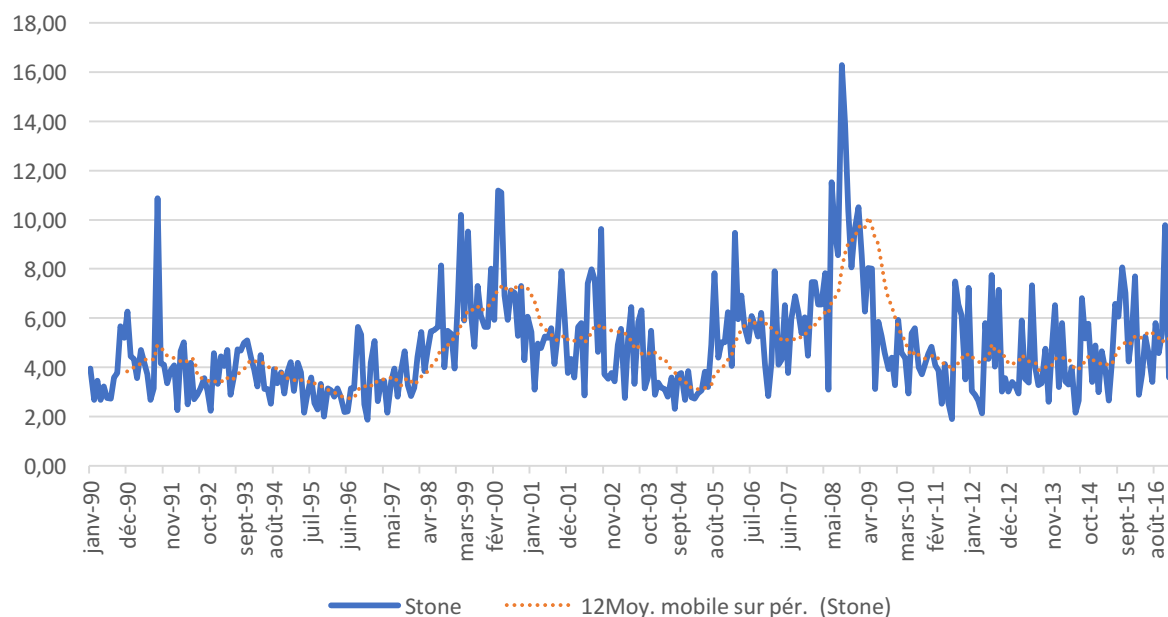


Figure 15 - Monthly idiosyncratic volatility of construction from 01/1990 to 03/2017

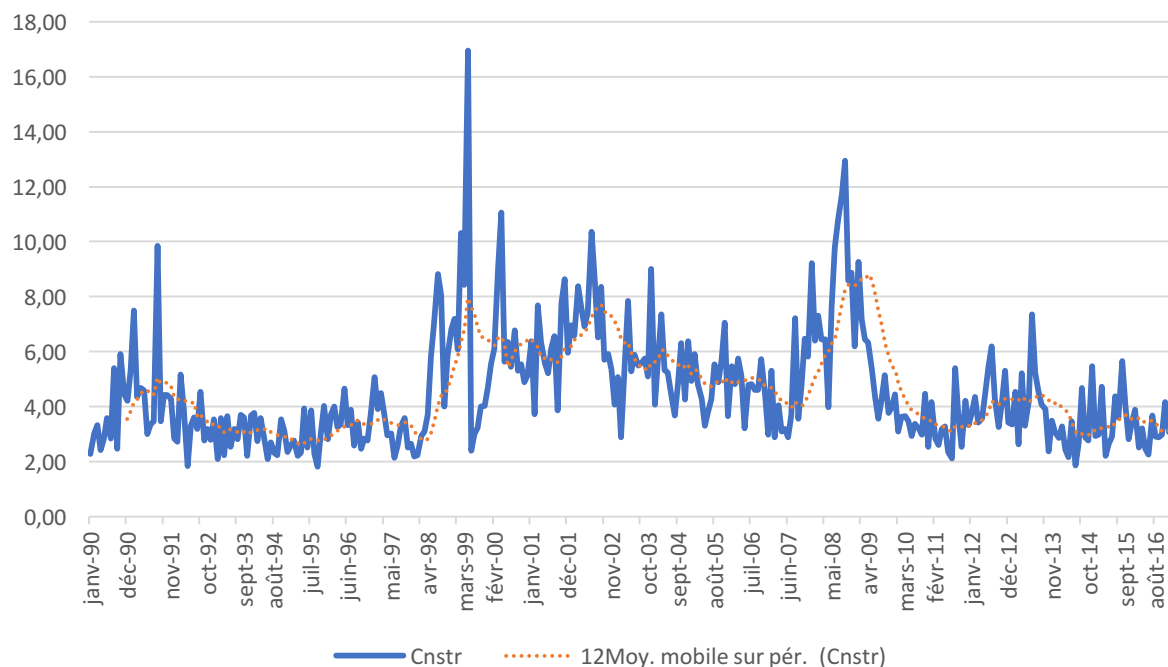


Figure 16 - Monthly idiosyncratic volatility of food from 01/1990 to 03/2017

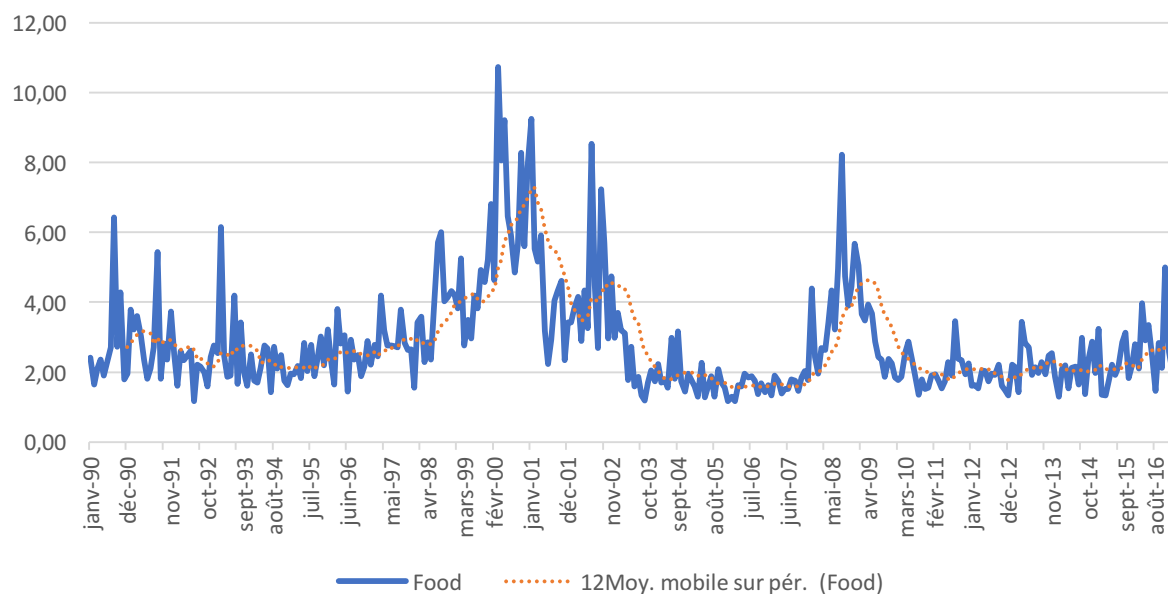


Figure 17 - Monthly idiosyncratic volatility of smoke from 01/1990 to 03/2017

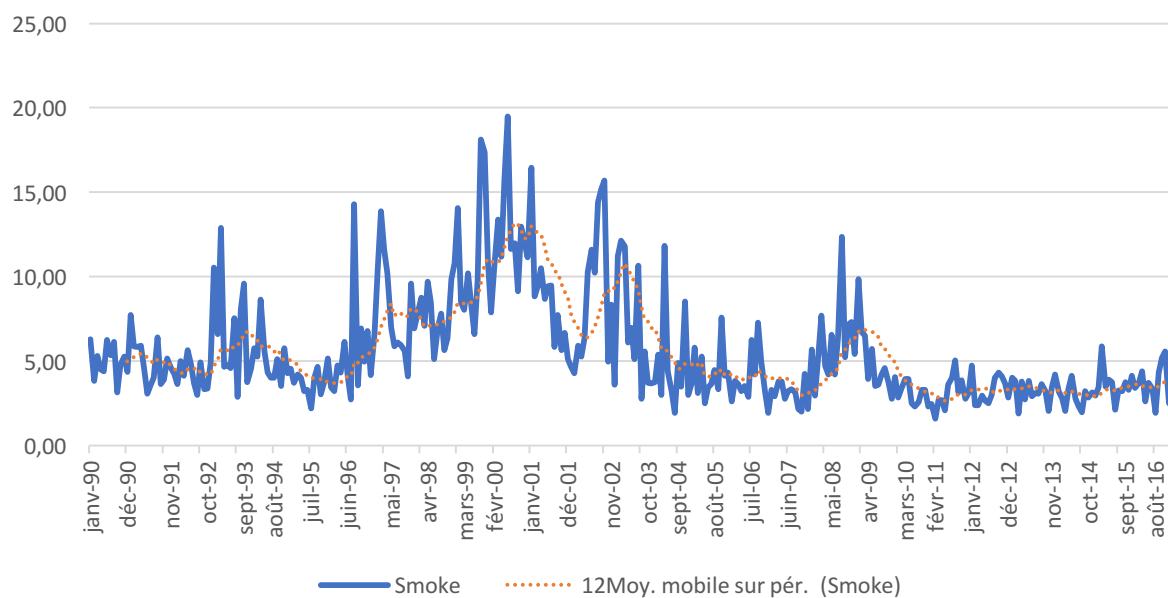


Figure 18 - Monthly idiosyncratic volatility of txtls from 01/1990 to 03/2017

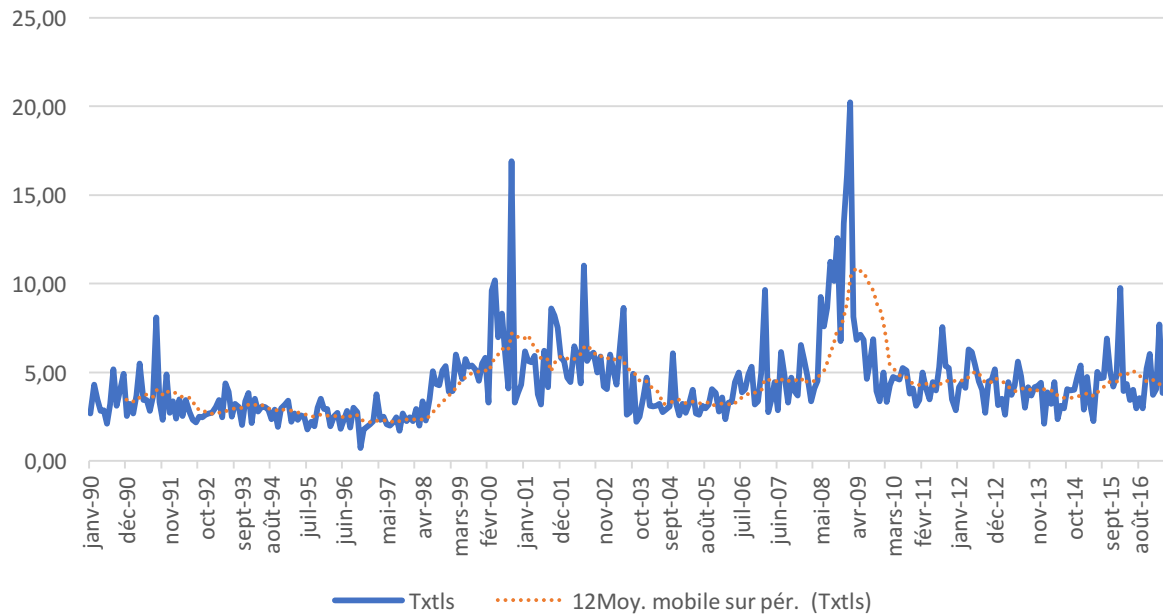


Figure 19 - Monthly idiosyncratic volatility of appr from 01/1990 to 03/2017

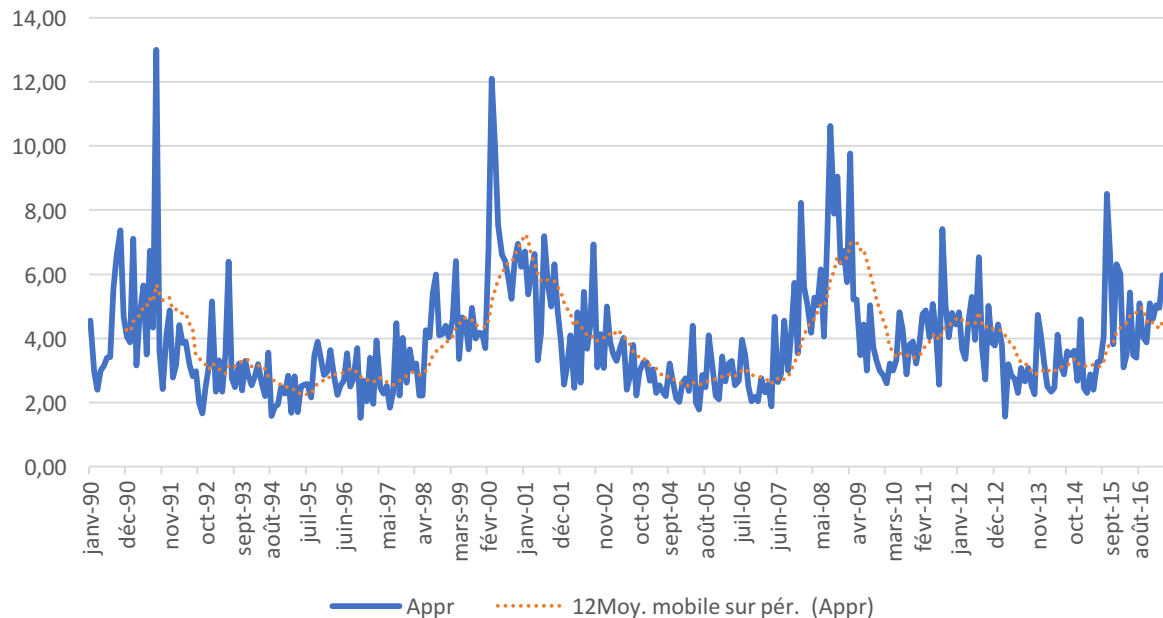


Figure 20 - Monthly idiosyncratic volatility of wood from 01/1990 to 03/2017

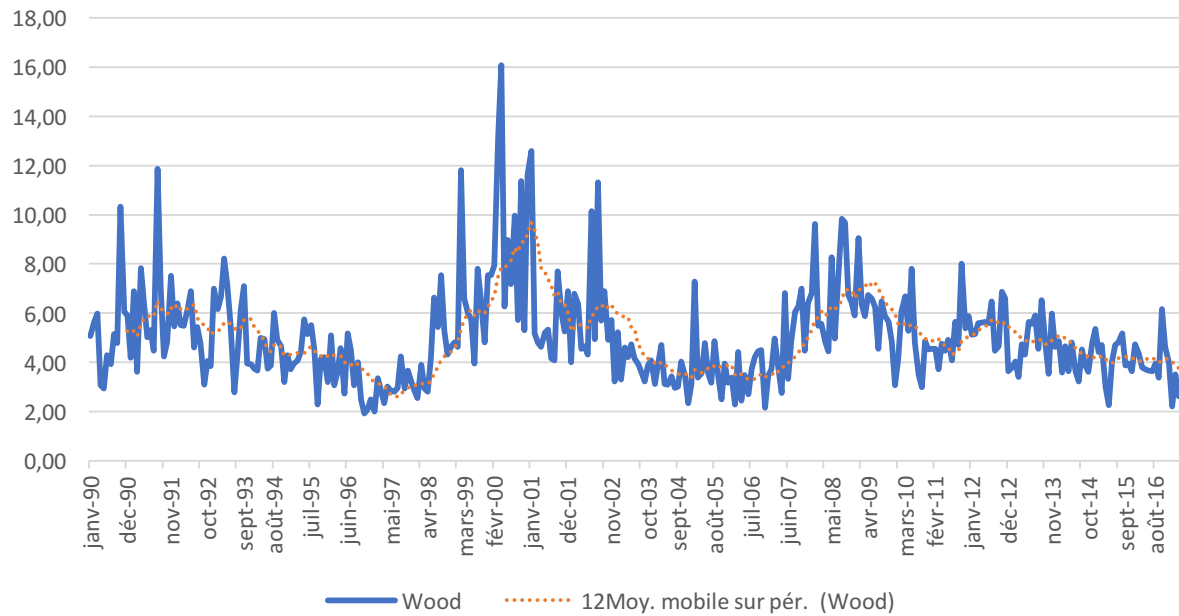


Figure 21 - Monthly idiosyncratic volatility of chair from 01/1990 to 03/2017

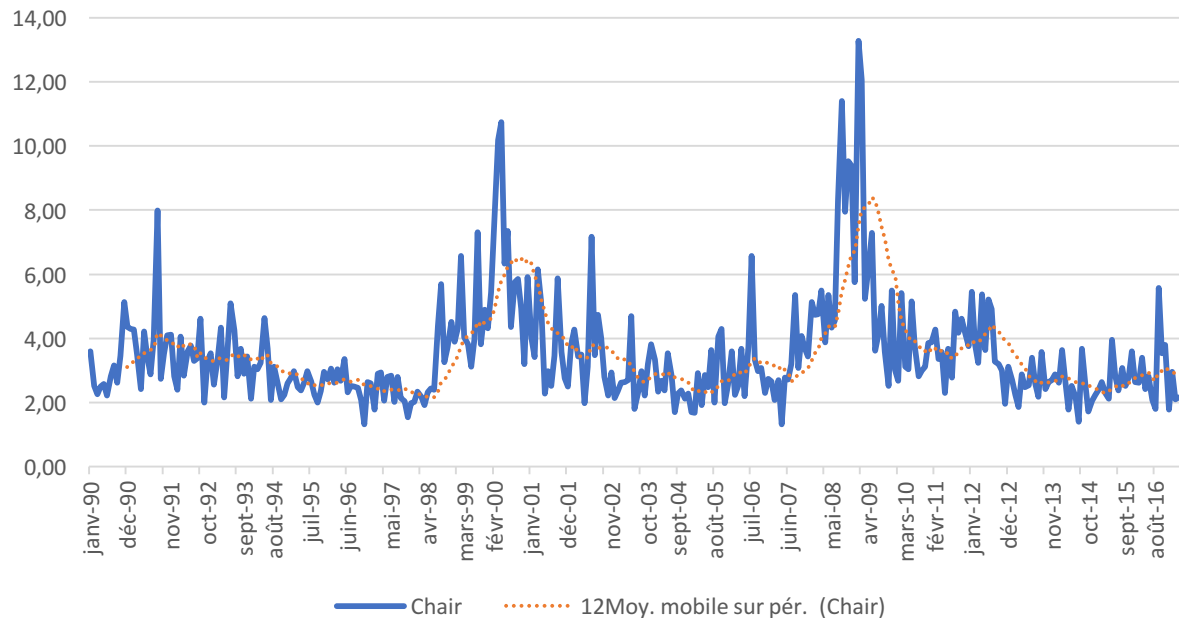


Figure 22 - Monthly idiosyncratic volatility of paper from 01/1990 to 03/2017

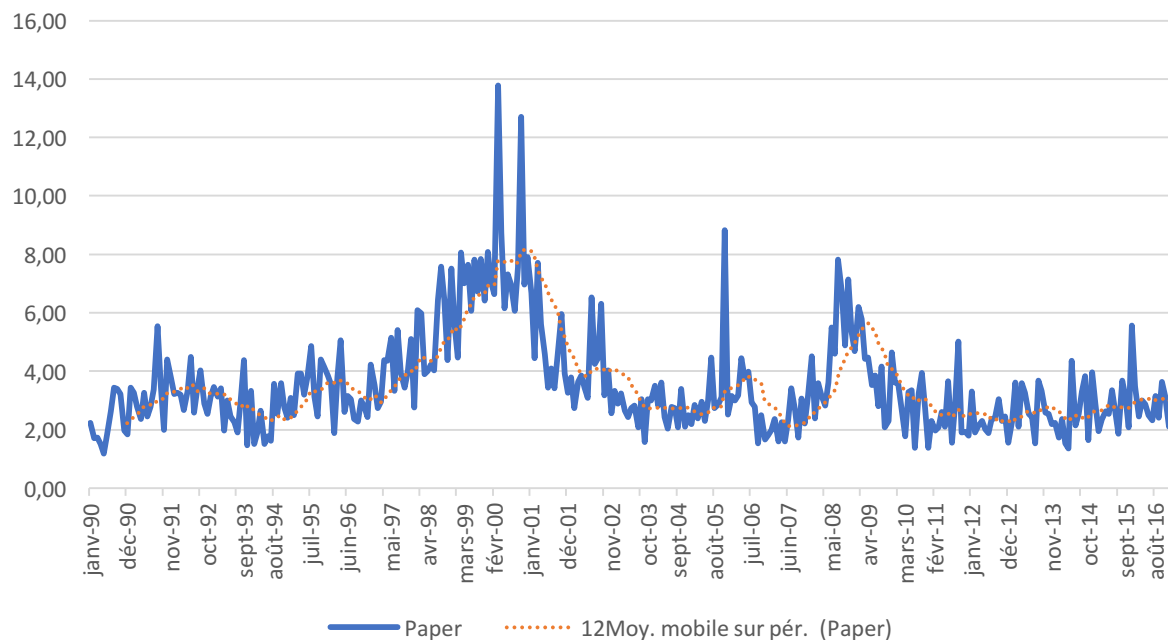


Figure 23 - Monthly idiosyncratic volatility of print from 01/1990 to 03/2017

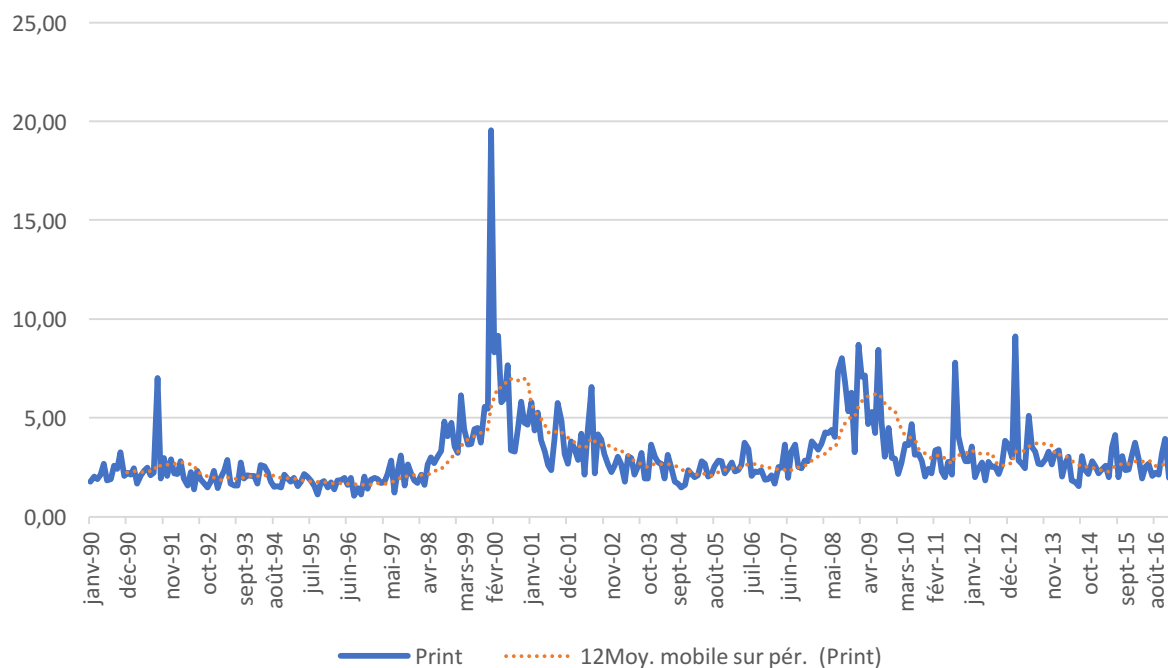


Figure 24 - Monthly idiosyncratic volatility of chems from 01/1990 to 03/2017

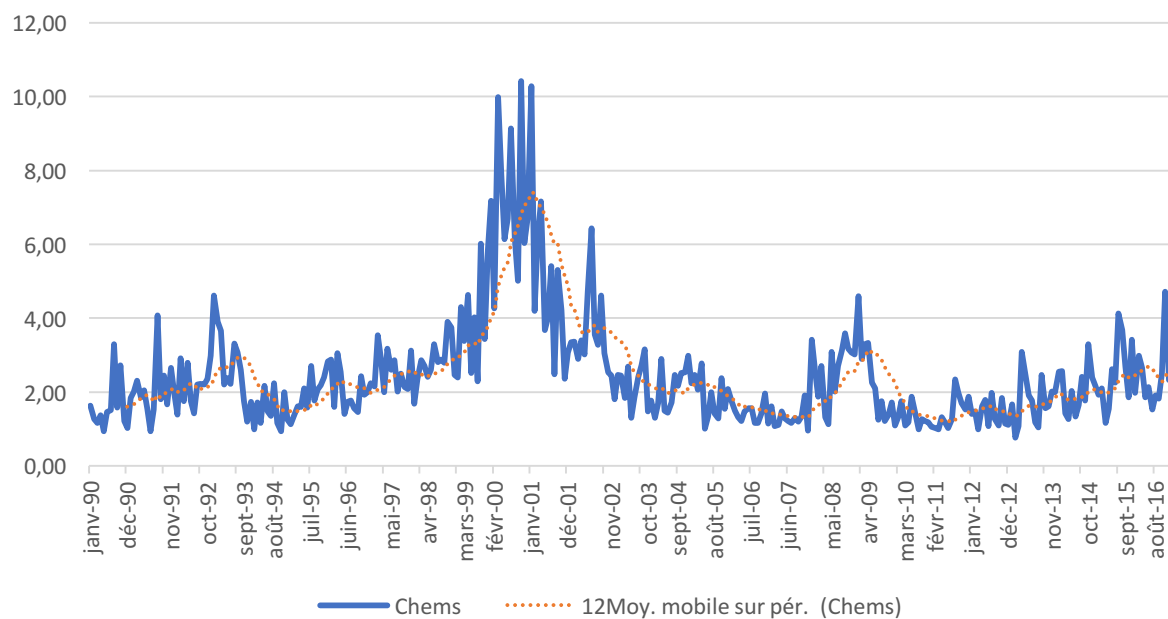


Figure 25 - Monthly idiosyncratic volatility of ptrlm from 01/1990 to 03/2017

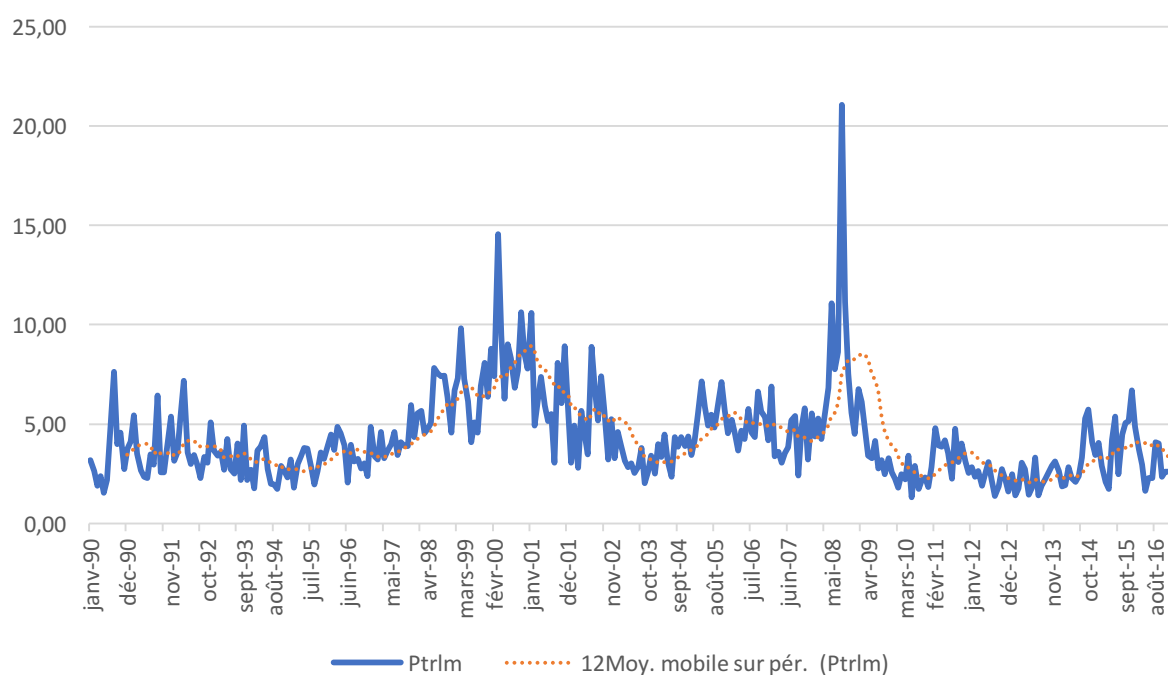


Figure 26 - Monthly idiosyncratic volatility of rubbr from 01/1990 to 03/2017

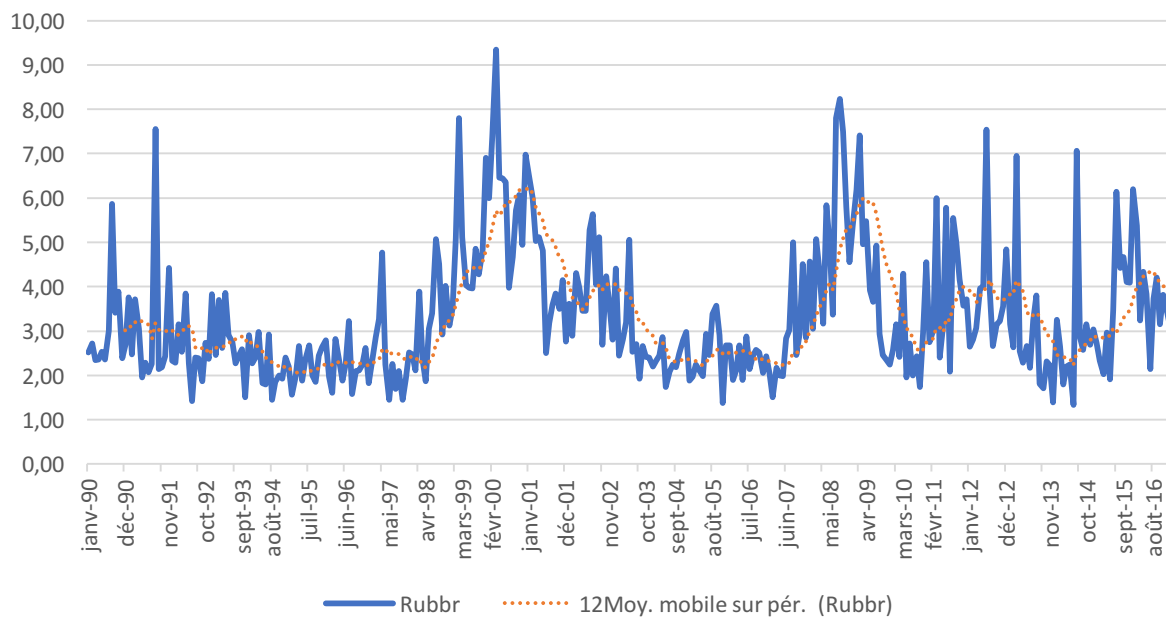


Figure 27 - Monthly idiosyncratic volatility of lethr from 01/1990 to 03/2017

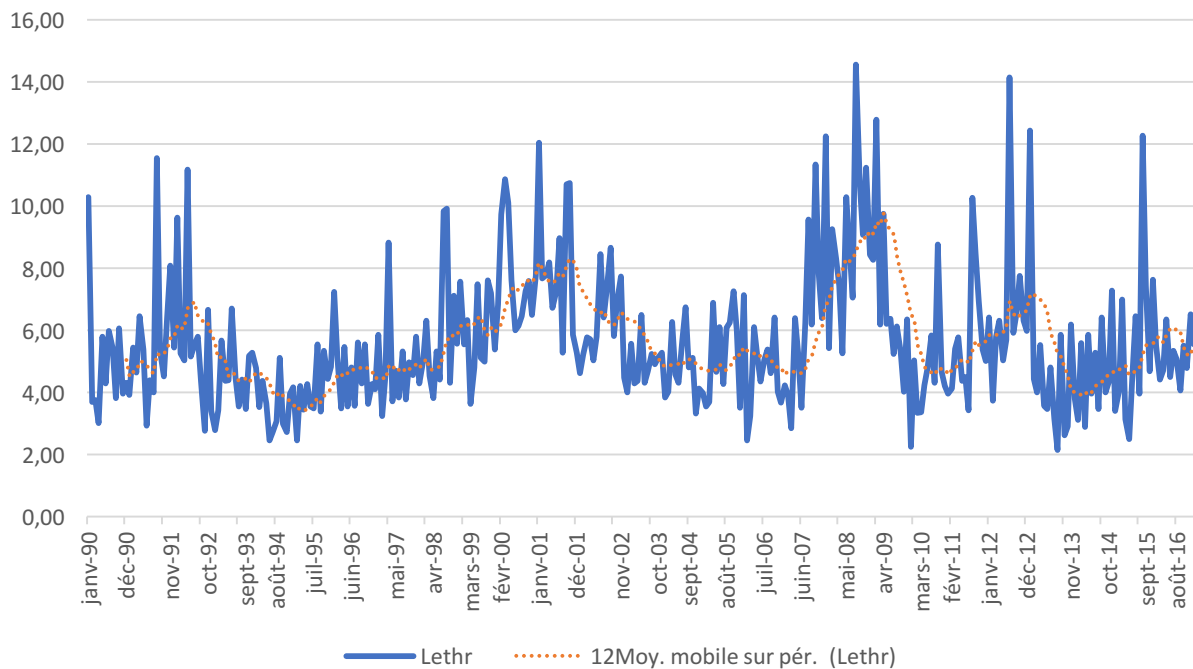


Figure 28 - Monthly idiosyncratic volatility of glass from 01/1990 to 03/2017

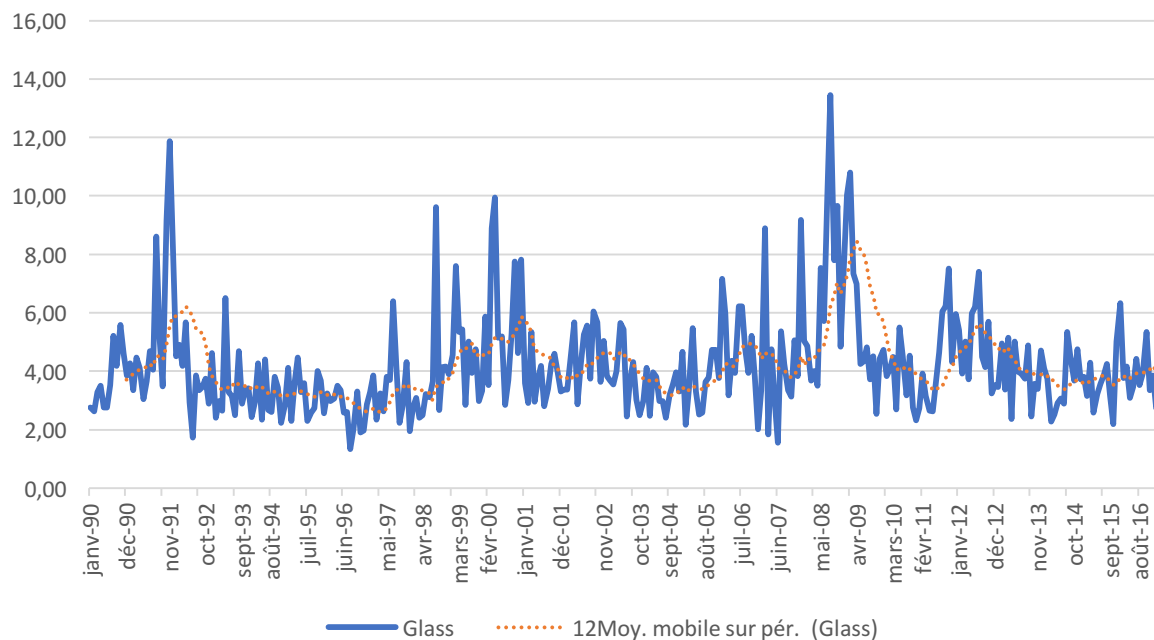


Figure 29 - Monthly idiosyncratic volatility of metal from 01/1990 to 03/2017

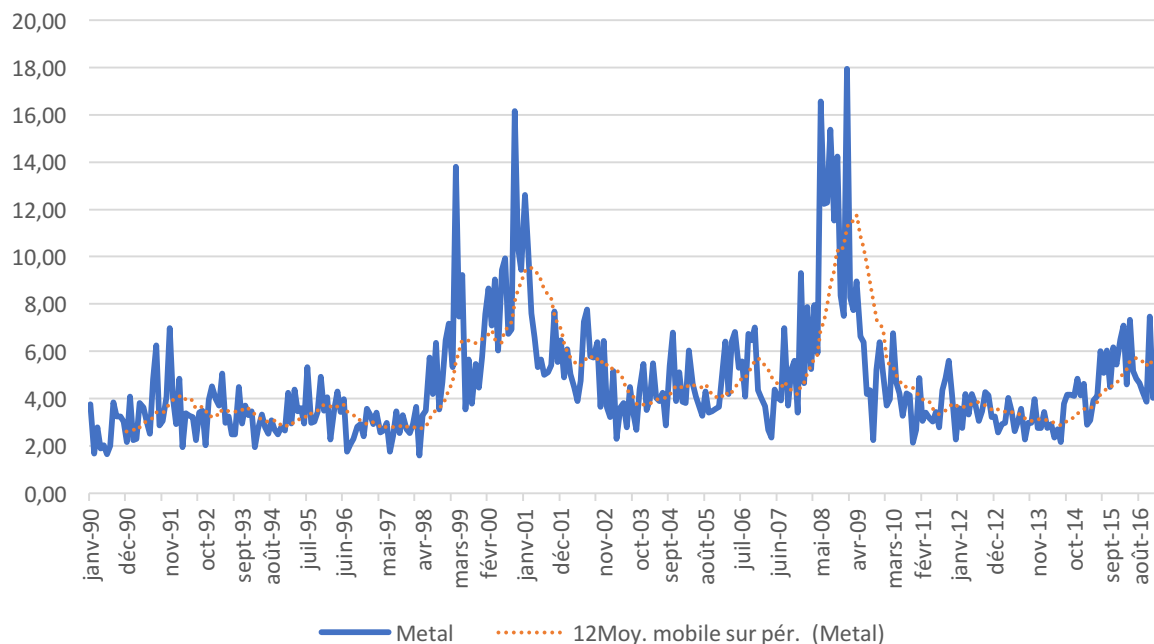


Figure 30 - Monthly idiosyncratic volatility of mtlpr from 01/1990 to 03/2017

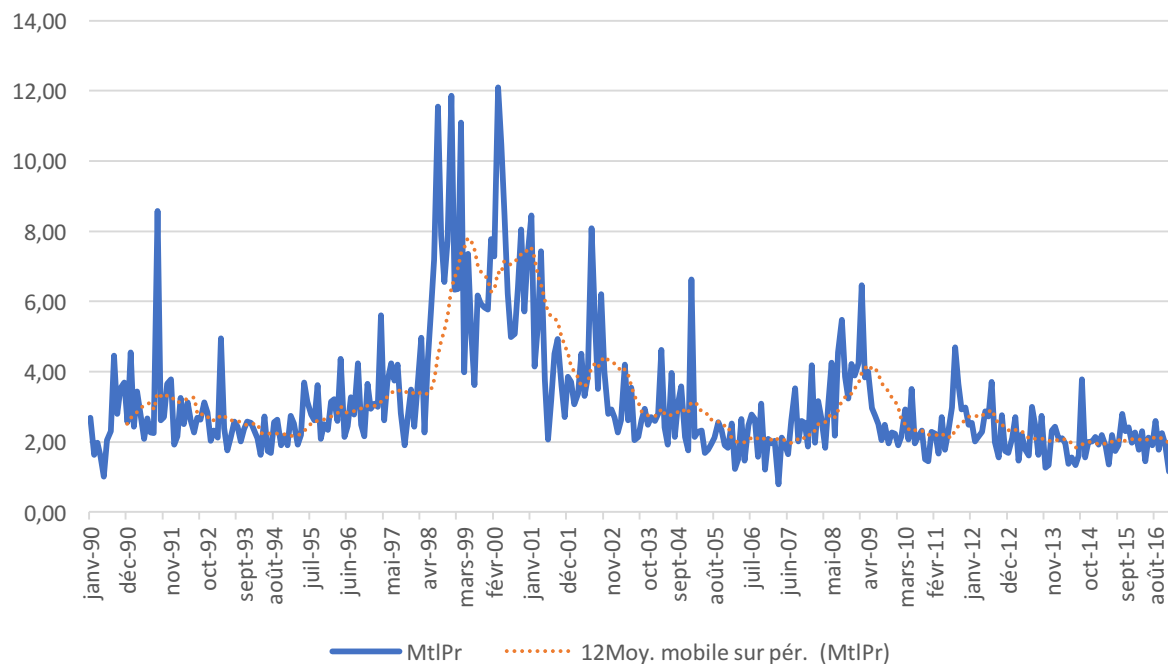


Figure 31 - Monthly idiosyncratic volatility of machn from 01/1990 to 03/2017

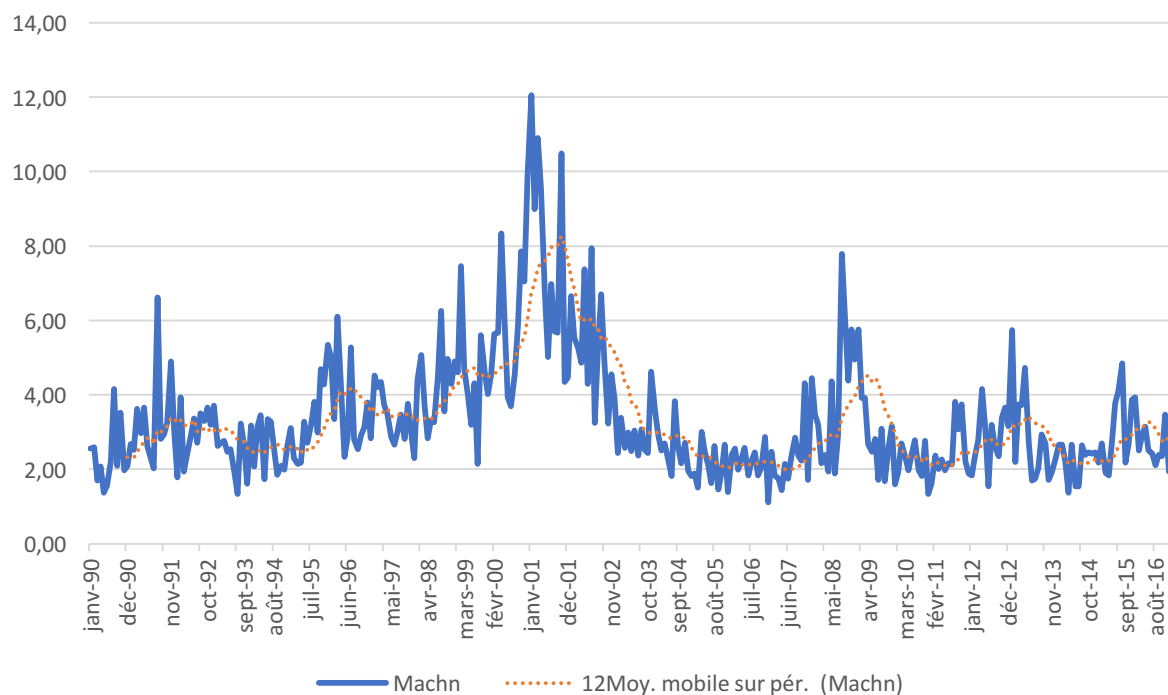


Figure 32 - Monthly idiosyncratic volatility of elctr from 01/1990 to 03/2017

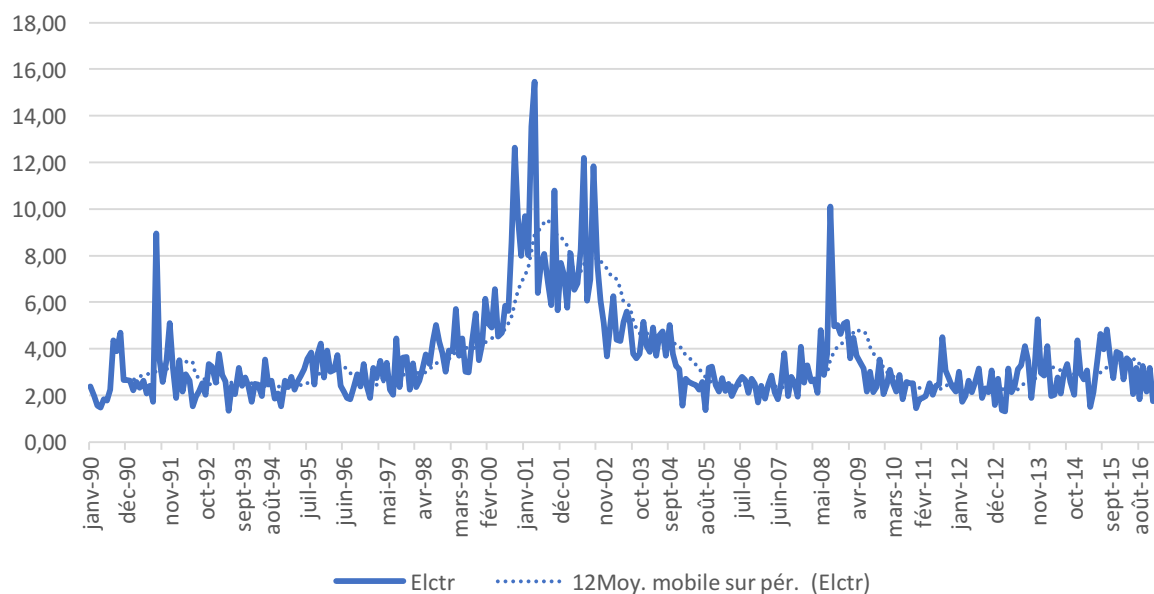


Figure 33 - Monthly idiosyncratic volatility of cars from 01/1990 to 03/2017

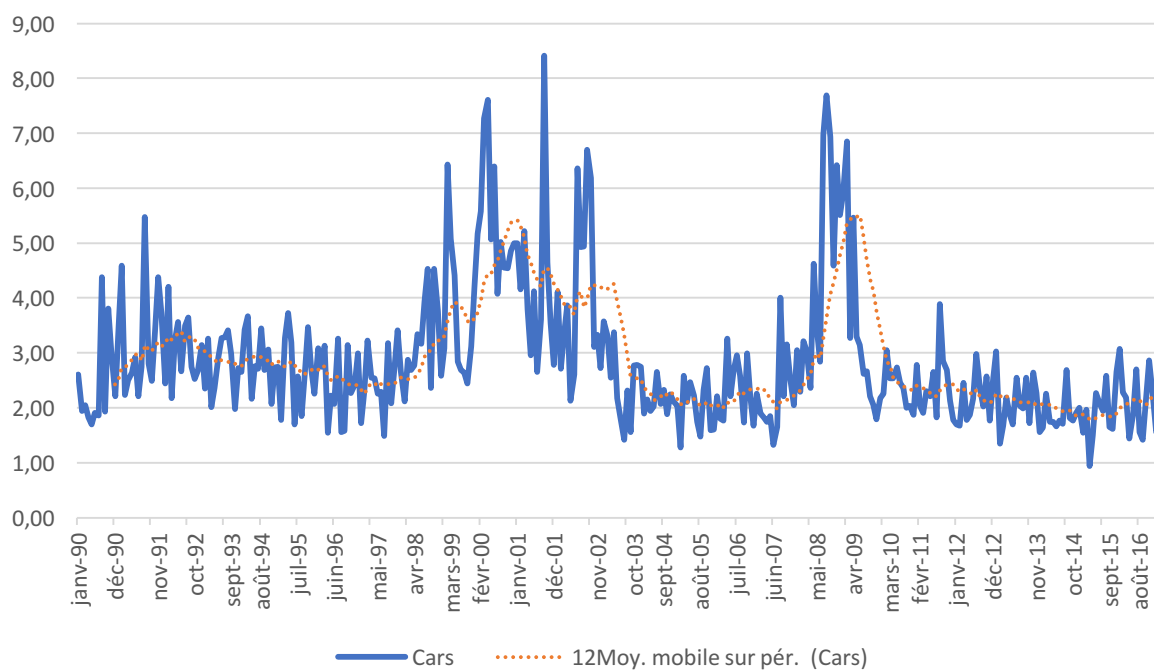


Figure 34 - Monthly idiosyncratic volatility of instr from 01/1990 to 03/2017

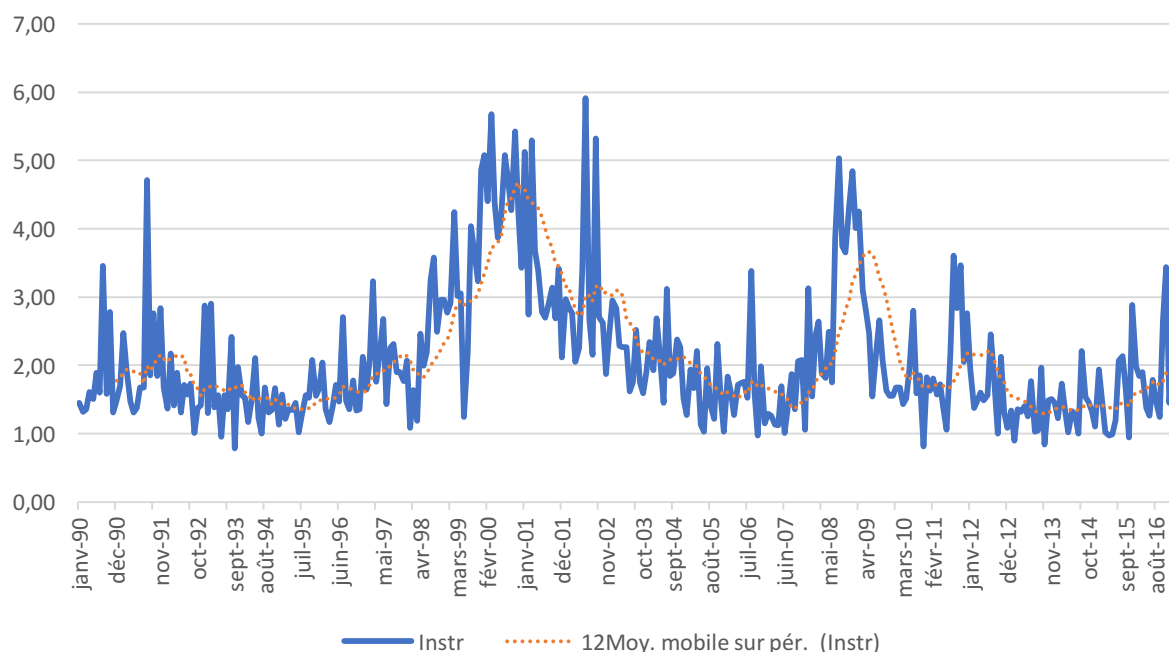


Figure 35 - Monthly idiosyncratic volatility of manuf from 01/1990 to 03/2017

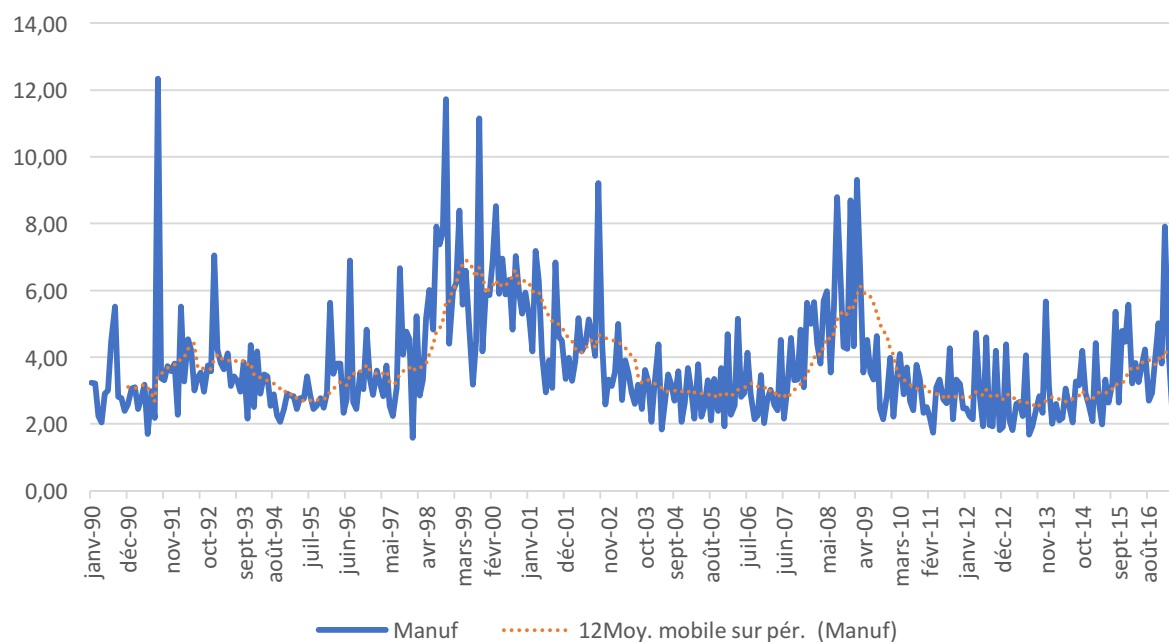


Figure 36 - Monthly idiosyncratic volatility of trans from 01/1990 to 03/2017

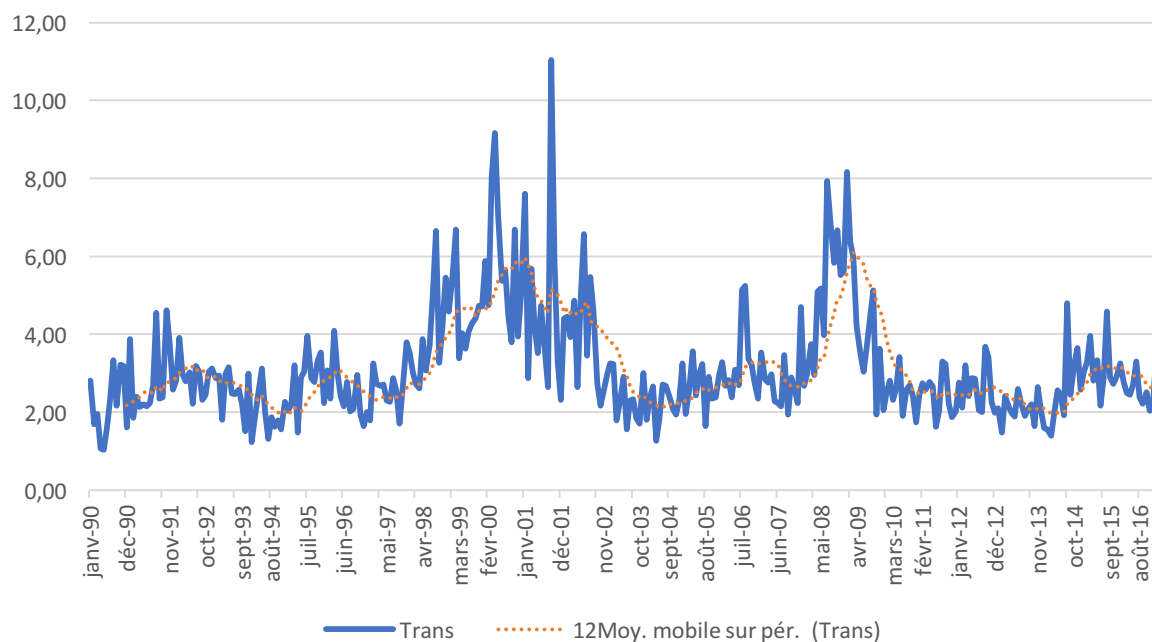


Figure 37 - Monthly idiosyncratic volatility of phone from 01/1990 to 03/2017

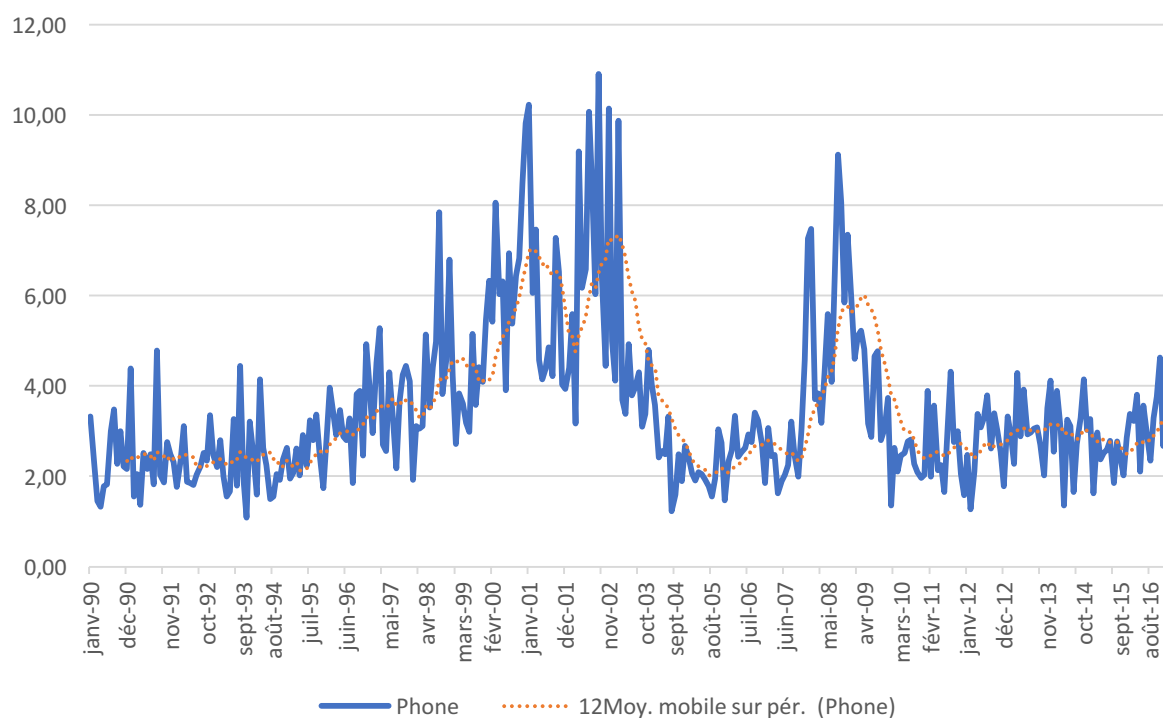


Figure 38 - Monthly idiosyncratic volatility of tvrf from 01/1990 to 03/2017

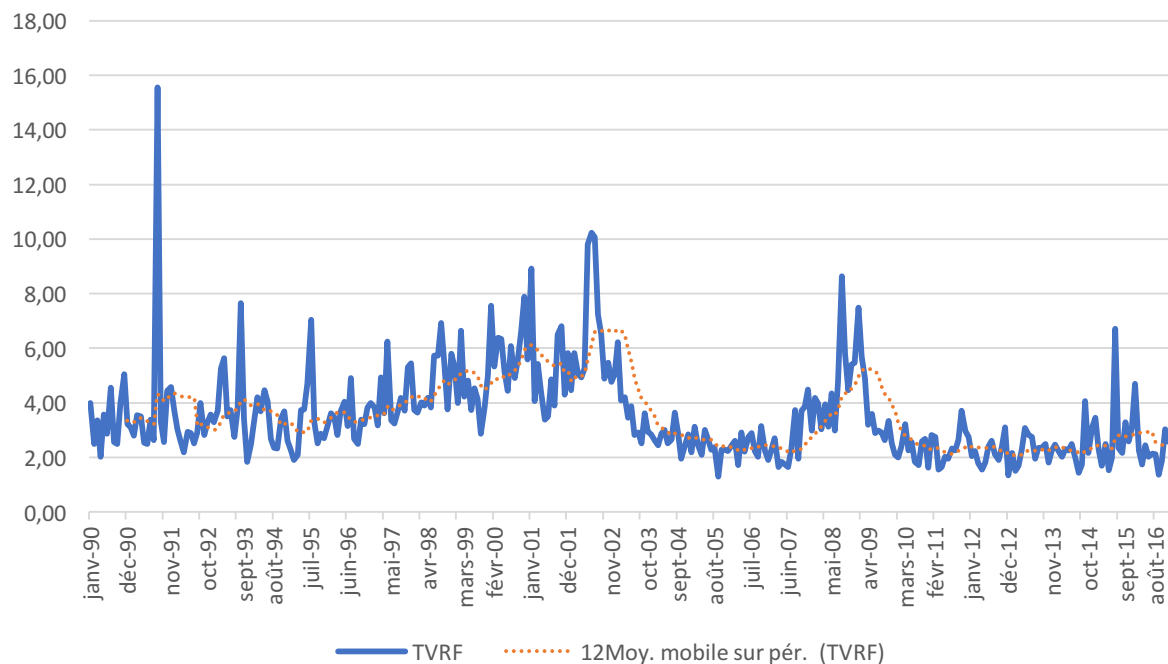


Figure 39 - Monthly idiosyncratic volatility of utils from 01/1990 to 03/2017

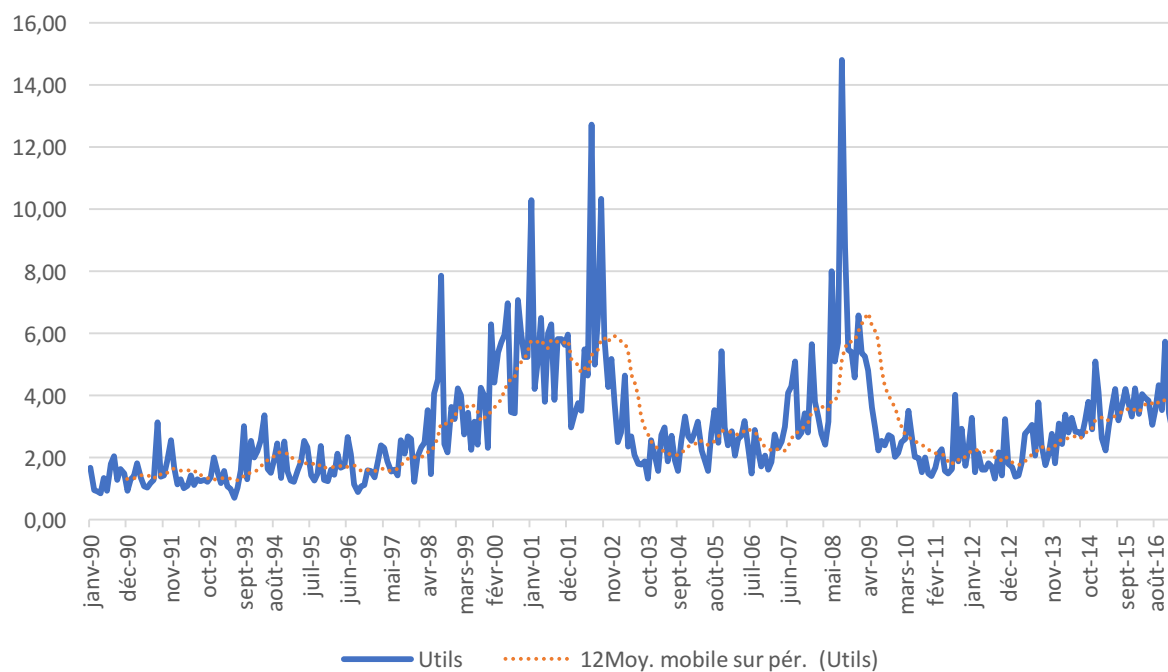


Figure 40 - Monthly idiosyncratic volatility of garbg from 01/1990 to 03/2017

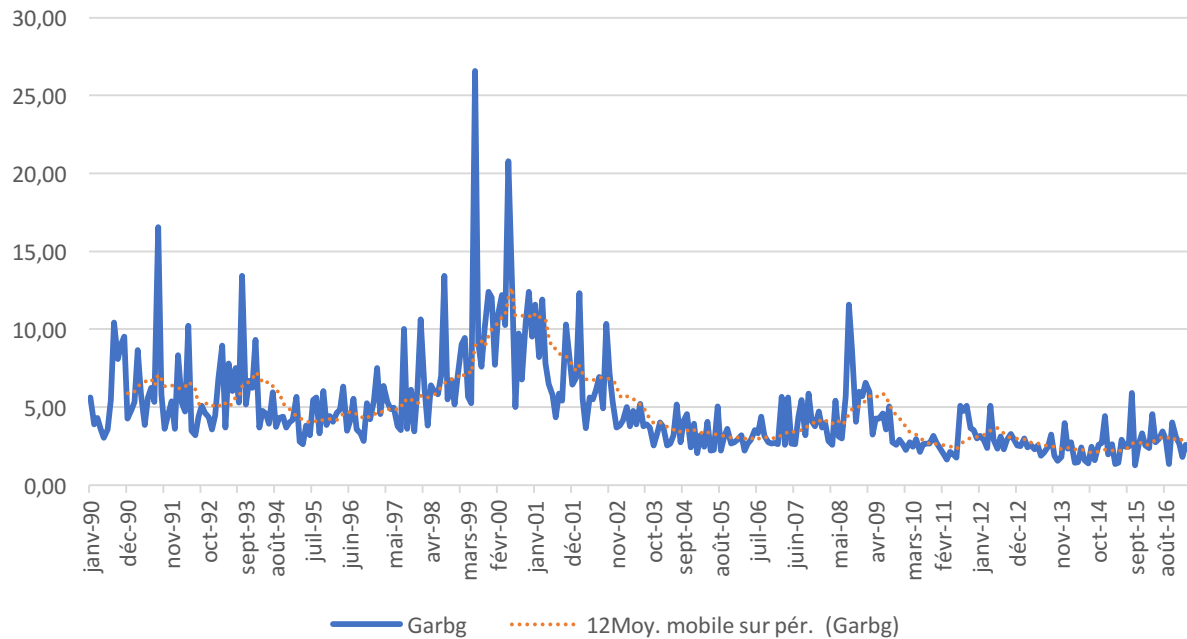


Figure 41 - Monthly idiosyncratic volatility of steam from 01/1990 to 03/2017

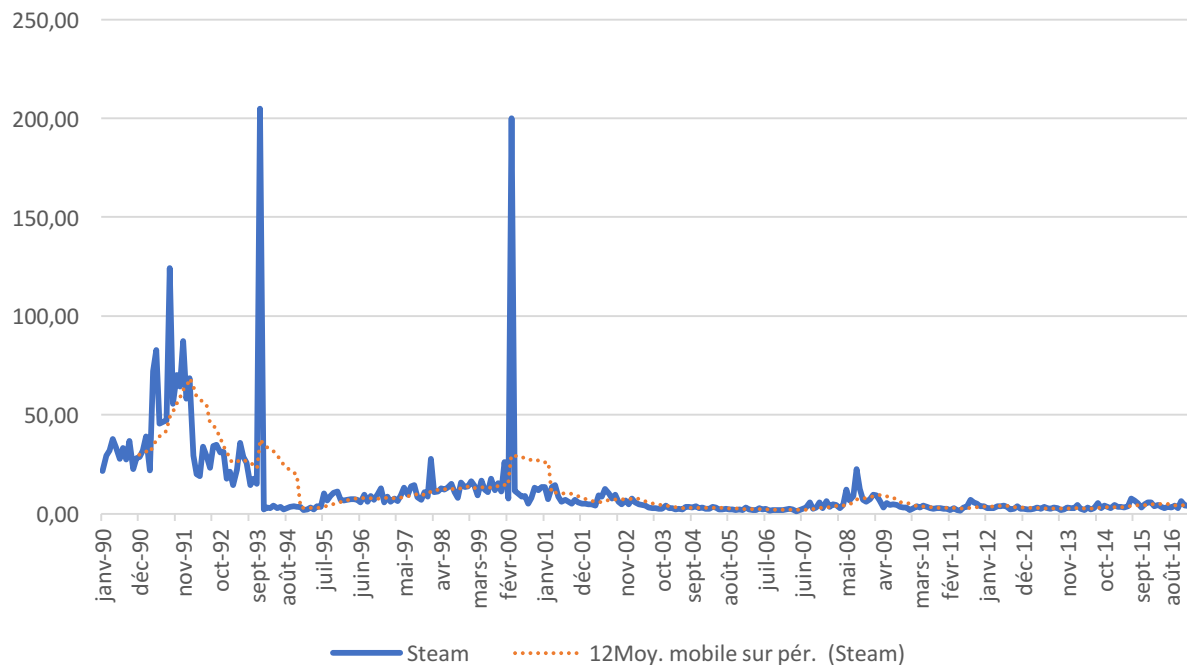


Figure 42 - Monthly idiosyncratic volatility of whlsI from 01/1990 to 03/2017

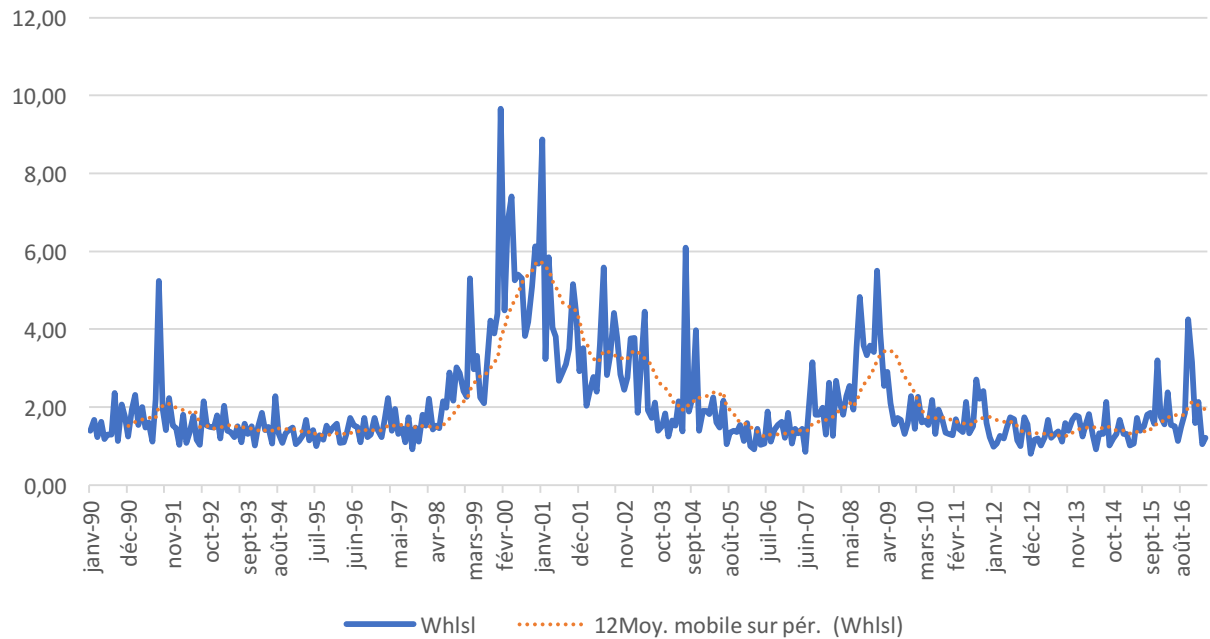


Figure 43 - Monthly idiosyncratic volatility of retail from 01/1990 to 03/2017

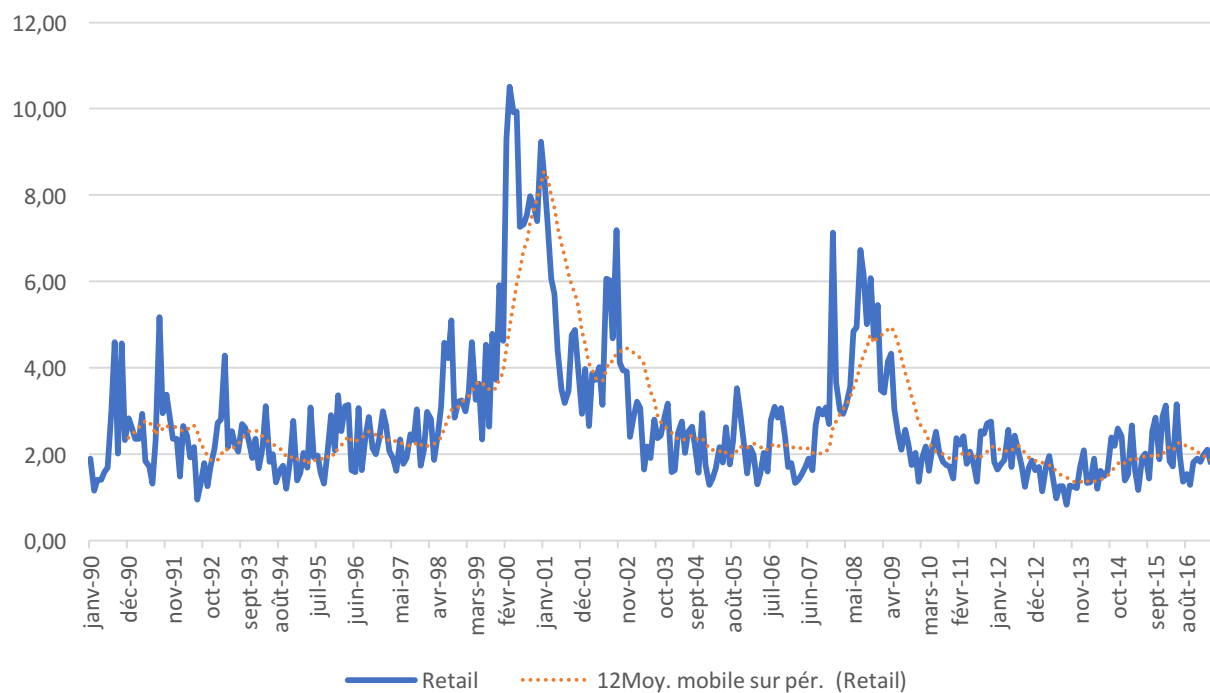


Figure 44 - Monthly idiosyncratic volatility of money from 01/1990 to 03/2017

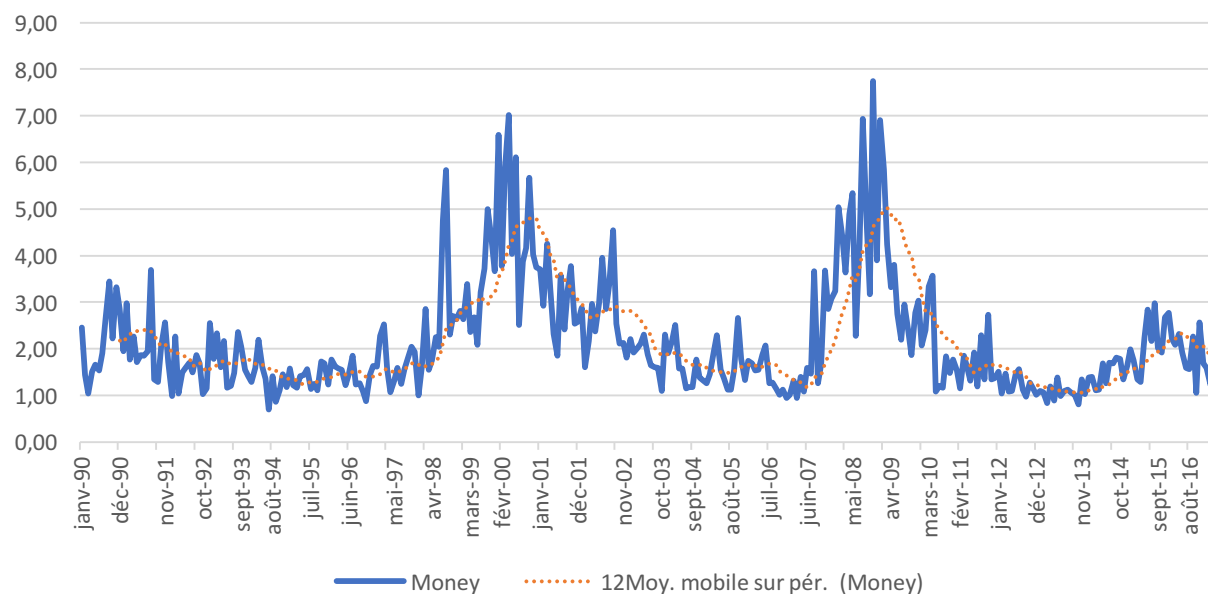


Figure 45 - Monthly idiosyncratic volatility of srvc from 01/1990 to 03/2017

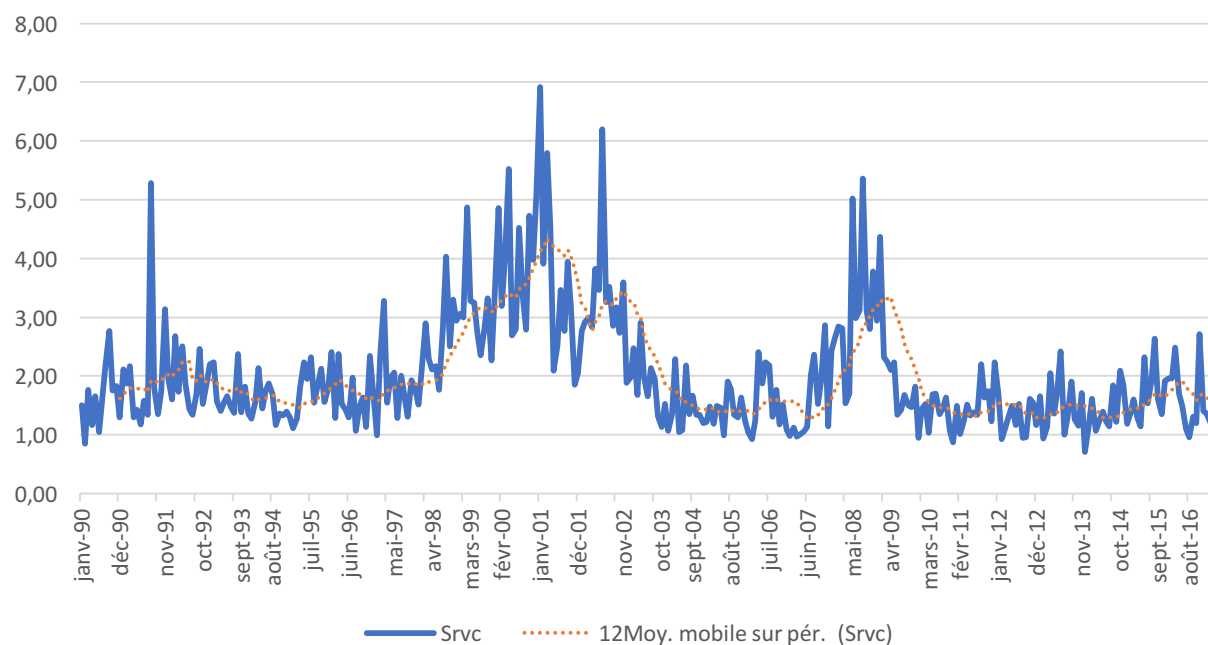


Figure 46 - Monthly idiosyncratic volatility of gov from 01/1990 to 03/2017

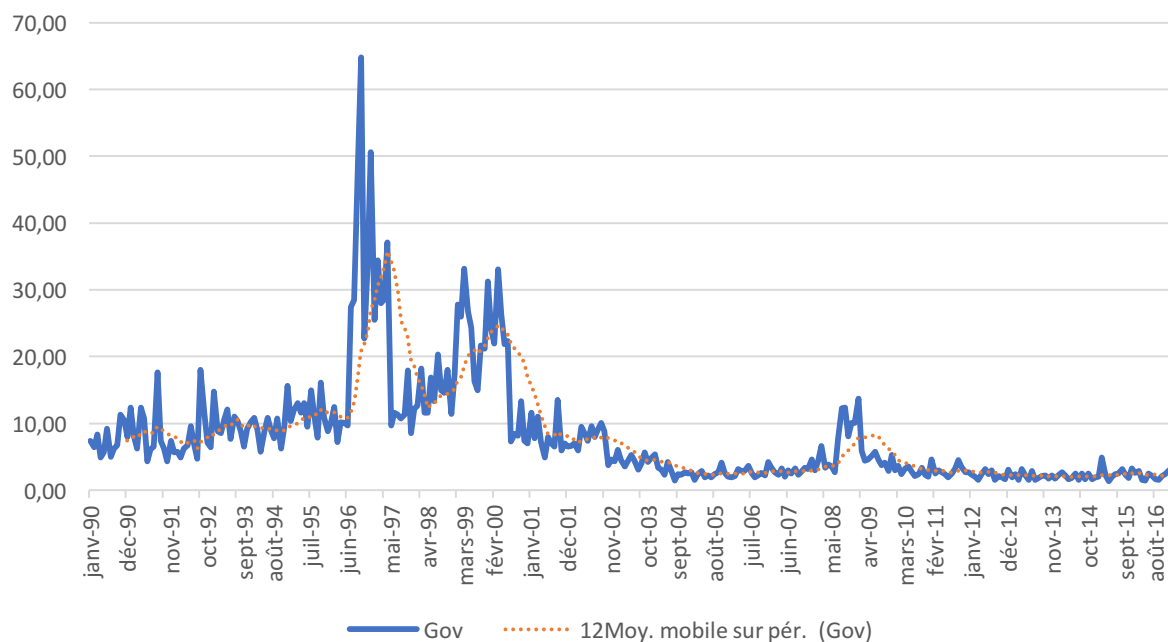


Figure 47 - Monthly idiosyncratic volatility of other from 01/1990 to 03/2017

