

To Deal or not to Deal

The Impact of Uncertainty on Corporate Finance Transactions

Lorenzo Anolli | 40967

December 2016

Stockholm School of Economics
Department of Finance | Master of Science in Finance
Master Thesis | Double Degree Program

Abstract

In this paper, we analyze to what extent uncertainty levels have historically impacted corporate finance transaction flows. Over 16 years and 8 countries, we first build an uncertainty index (UIX) and then we put it to work to assess the effect of uncertainty on debt issuance, equity issuance, and mergers and acquisitions. After controlling for factors considered relevant in literature, we find a significant and substantial negative impact on corporate debt issuance and IPOs. We also find that this recess in corporate financing is not explained by fluctuations in investments or loans at the broader economy level. Our interpretation is that uncertainty is a relevant factor only in the cases when delaying or pulling a deal is a feasible option - after considering break-up costs, time constraints and the nature of contracting parties involved. Furthermore, the series affected by uncertainty are the ones where uncertainty-driven activity is more difficult to imagine (e.g. the fire sale of a division). We conclude that uncertainty is a factor that mainly poses problems to the

pricing and placement to market of corporate debt and equity initial public offers,
as it is mostly relevant for public investors facing information asymmetry.

Supervisor: Professor Mariassunta Giannetti

Keywords: uncertainty, IPO, corporate debt, corporate finance transactions, volatility,
policy uncertainty

And, like a man to double business bound,
I stand in pause where I shall first begin,
And both neglect.

W. SHAKESPEARE, HAMLET, ACT 3, SCENE 3

Acknowledgments

First of all, I would like to sincerely thank my supervisor Professor Mariassunta Giannetti for her support and precious advice throughout the steps of this work.

I would also like to express my gratitude to Professor Gianfranco Gianfrate, for his guidance and help during the progress of this project.

Finally, I owe my deepest gratitude to Matteo Leombroni, for sharing with me his passion for the topic.

To my parents.

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1 Introduction

1.1 Uncertainty in the Financial Markets

Uncertainty is the economic agents inability to evaluate probabilities associated to future events. A certain level of uncertainty is inherent to any business and financial activity - as it is inherent to life - due to the open and non-bounded nature of the future. However, this level varies over time for many different reasons, as a consequence for example of political or economic shocks, or following the cycle of expansions and recessions.

Differently from risk, pure uncertainty - by definition - can never be priced with sufficient confidence, and as such remunerated. Therefore, it is usually taken into great consideration and actively avoided by decision makers in the economy. Indeed, it is well documented that individuals are uncertainty averse, and a spike in uncertainty should in principle instill caution in agents and have a negative effect on market activity, investment and business in general.

Despite being a source of opportunities for market makers and derivatives traders, periods of uncertainty are feared on the corporate side of investment banks, because they can quickly translate into lower deal activity as clients get cold feet and suspend any non-ordinary activity. Indeed, industry specialists and journalists usually consider uncertainty a leading indicator of deal flow, even after taking into account the impact of other correlated macroeconomic variables.

Popularity of uncertainty mentions in the financial press and literature is somehow short-lived, and part of the legacy of the 2008 Great Recession. It is believed to have received full legitimacy when it was quoted by Standard & Poor's as one of the reasons that led to the downgrade of the US sovereign debt in August 2011. Afterwards, all the major financial shocks have been analyzed also in light of their expected fallout on uncertainty.

In the last few years, literature has extensively studied the characteristics of uncertainty and its impact on economic variables, both on a macro and micro level. There are many studies that investigate how firms react to uncertainty in their investment and financing decisions; and how this is reflected into the economy. On the other hand, there

are also many studies that try to explain cycles in corporate finance transaction flows, linking them to fundamental economic variables or behavioral patterns, and only marginally referring to uncertainty-related measures. This paper tries to fill the gap between these two research areas, studying to what extent uncertainty has historically had an impact on the debt and equity capital markets instruments issuance as well as on mergers and acquisitions activity.

This paper builds extensively on the work on uncertainty done by Nicholas Bloom in the last few years. We extend the application of the Economic Policy Uncertainty index¹ to a new, specific, research area that has the advantage of displaying a good degree of data availability and practical business relevance.

1.2 A Recent Example of an Uncertainty Shock: the Brexit Referendum

On June 23 2016, the United Kingdom voted to leave the European Union in a referendum, defying all expectations that had lately converged on a remain win. Within the following week, almost every major political leader in the UK (including PM Cameron) resigned, and Northern Ireland and Scotland independence parties threatened new referendum polls. Political reaction from mainland Europe was ambiguous, as speculation on the stability of the European Union as a whole, especially the periphery, exploded. The role of London as Europe financial center was suddenly at stake. Nobody really knew what was going to happen, and when, as for the first few months, nobody had a clue about what sort of deal would have been struck with the EU, especially regarding single market access and financial services passporting rights.

Immediately, an uncertainty shock wildly reverberated through the financial markets², and as ballots were counted, industry professionals and observers reviewed sharply downwards their short-term expectations for the corporate finance transaction flows. The

¹The Economic Policy Uncertainty index (Baker, Bloom and Davis, 2012) is here used indirectly to build an uncertainty index via a principal components analysis.

²The British Pound lost approximately 20% of its value against the US Dollar in the following months, while the FTSE 100 trended slightly up in GBP terms. At the time of writing, it is too early to assess the impact of the shock on UK macroeconomics.

purpose of this paper is indeed to assess to what extent these fears were historically motivated.

In the following months, companies financial reports and official statements quickly got populated with the word “uncertainty” in conjunction with Brexit commentary, and financial journalists started quoting “uncertainty” as the main reason behind every market negative movement or failed deal. For example, in the UK in October, three companies (Misys, Pure Gym Group and TI Fluid Systems) said they pulled already announced IPOs amid uncertainty, despite market valuations, interest rates and macroeconomic indicators seemed at historically favorable levels.

When the dust settles, it will be interesting to study the propagation and fallout of Brexit from an academical perspective, as from the current standpoint it seems like this shock is primarily an uncertainty shock. A big and primary uncertainty shock is not a very common combination, because levels of uncertainty of this size are usually a second order effect of financial or macroeconomic movements.

1.3 The Uncertainty Index (UIX)

In order to analyze the impact of uncertainty on transactions, a quantitative measure of this phenomenon must be identified.

Despite uncertainty being a non-measurable object, many proxies have been used in literature over the past decades. Of paramount importance are market indices on the basis of the assumption that markets price in real time the state of the world and the beliefs of agents. However, non-market based indicators have earned a good considerations lately. They are particularly important in this period because market variables are endogenously distorted by central banks policies, and non-market based indicators can give a useful supplementary view on the underlying uncertainty agents actually face.

Among these, our analysis will make use of the Economic Policy Uncertainty (EPU) index. Developed by Baker, Bloom and Davis (2012), it is one of the most widely adopted non-financial indicators of uncertainty. By way of introduction, it is a synthetic measure of the frequency of uncertainty related economic news in major newspapers, and will be explained in more detail in the following pages.

To carry out our analysis, we build an uncertainty index (UIX) by taking the first principal component of a matrix including the above mentioned EPU index, the implied volatility of the domestic stock market, the implied volatility of the domestic currency, and the realized volatilities of the returns on the domestic equity index, the domestic currency and the 10-year reference government interest rates.

Our index displays three fundamental characteristics: (i) cross-country correlations are very high; (ii) it is persistent; (iii) it is right-skewed. These features well represent what is known about uncertainty in literature such as uncertainty spillovers between countries, and the fact that uncertainty increases in jumps and then slowly decreases as circumstances revert to normal. Furthermore, we show that the UIX and the VIX³ are highly correlated.

1.4 A Comprehensive Analysis of the Impact of Uncertainty on Corporate Finance Transactions

Corporate finance transactions are extraordinary operations executed by corporates on the debt and equity public markets and on the corporate control markets. Most common examples are: equity and debt (i.e. corporate bonds) placement on public markets, mergers, acquisitions and disposals. Since this kind of operations are complex and uncommon for the average firm, they are generally performed with the help of investment banks and other advisers that are able to provide many different tailored services (e.g. strategic and negotiation advice, access to investors or counter-parties, deal marketing support, access to market via book-building capabilities, bridge financing and hedging).

These corporate finance transactions are known to happen in waves. Academic literature has studied the phenomenon extensively, finding both fundamental and behavioral explanations behind this pattern. Economic growth, capital market activity and interest rates are commonly referred to as relevant factors when looking at the fundamental side of the debate. Market (mis-)valuation is instead one of the key parameters observed on the behavioral side of the discussion. Some studies on initial public offerings also ex-

³The implied volatility index calculated with CBOE methodology, using options on the stock market index.

plicitly account for uncertainty⁴. However, their analysis is limited to a single product (IPO) and a single geography (United States), and they use different, partial indicators of uncertainty.

In our study, we aim at identifying the average impact of uncertainty on a series of different corporate finance transactions, ranging from debt and equity issuance to merger and acquisitions. Through a panel linear regression model, we analyze a monthly data-set spanning across sixteen years (Jan-2000 to Dec-2015) and comprising eight countries: United States, European Union (limited at monetary union level), United Kingdom, Japan, South Korea, Canada, Russia, and India.

We control for the risk appetite in the markets (i.e. level of the stock market), the status of the economic cycle (i.e. level of industrial production or GDP), the cost of money and monetary policy stance (i.e. period change in 10-year government reference yield), the auto-correlated nature of the series (i.e. an AR(1) term) and the seasonality of business (i.e. monthly dummies).

We find that uncertainty has a significant and relevant negative effect on corporate debt issuance and IPOs, while it is negligible or not reliably confirmed on the rest of the analyzed series (i.e. government debt issuance, mergers and acquisitions, and equity capital markets as a whole).

For every standard deviation of uncertainty above its mean, the negative impact is in the region of 8-9% of the geometric mean for corporate bonds. For what concerns IPOs, the impact is around 30% when calculated in monetary terms, and limited at 11% when computed as number of deals (i.e. the average IPO is smaller when uncertainty is higher).

We also find that the behavior of investments and loans in the economy is not able to explain the fluctuations of these variables, leaving uncertainty both significant and relevant on corporate debt issuance and IPOs. We prove that results are robust to different specifications of the linear regression model.

⁴For example, Lowry (2003) uses uncertainty calculated as the dispersion of abnormal returns around earnings announcements and the dispersion of earnings analyst forecasts, as a proxy for information asymmetry; Pastor and Veronesi (2005) measure uncertainty via two proxies related to return volatilities of the firms just listed on the markets, and to the ratio between market and book value of equity.

Our reading is that uncertainty remains relevant only when the possibility of delaying or pulling a deal is realistic after taking into account costs, time constraints and the nature of parties involved. For example, an M&A deal can be more subject to negotiation-specific uncertainty than to uncertainty at a macro level, and pulling it may result in break-up fee and reputation costs. Where potential uncertainty-driven developments are common, the impact of uncertainty is non-significant: this is the case, for example, of a right-issue recapitalization in the broader equity capital markets family, a Keynesian debt-financed investment plan in government debt issuances, or a fire-sale of a non-core division in M&A. We conclude that uncertainty, being a factor mainly problematic for the pricing and placement to market of corporate debt issuance and equity initial public offers, is mostly relevant for public investors facing information asymmetry.

1.5 Structure of the Paper

The rest of the paper is organized as follows.

In Section 2, we analyze existing literature on the nature of uncertainty, its impact on different aspects of the economy, and on the structure and determinants of transaction waves in corporate finance.

In Section 3, we introduce our measure of uncertainty, with both qualitative and quantitative considerations. We illustrate its main features, and the interpretation of its value.

In Section 4, we go through our analysis of the impact of uncertainty on corporate finance transaction waves, with a thorough discussion of data, methodology and results. We include results diagnostics and robustness tests. We also extend our analysis to a quarterly model, in which we analyze how the investments and loans in the economy affect our results, in order to help us derive more meaningful conclusions on the previous findings.

In Section 5, we comment on the results, explain the limitations of our analysis, while highlighting areas for further research, and conclude the paper.

2 Literature Review

Literature on the topics discussed in this paper is abundant yet diverse. In this section we focus on: (i) the meaning and characteristics of uncertainty; (ii) literature discussing the impact of uncertainty on various business activities; and (iii) literature concerning the determinants of corporate finance transactions fluctuations over time.

2.1 The Meaning and Characteristics of Uncertainty

2.1.1 Definition of Uncertainty

In general terms, uncertainty emerges in any situation in which there is imperfect information. It is a term commonly used in many different fields and it is a feature of the world we live in, unavoidable when the object of the discussion is not completely observed. This aspect of life has stimulated brilliant philosophical dissertations over the course of history, but this is beyond the scope of this paper.

In economics and finance, uncertainty is usually defined as a situation in which the available knowledge is such that the state of the world is unknown, future events are unpredictable, and a set of probabilities cannot be matched to a set of possible outcomes in a credible way.

In simple terms, uncertainty is the inability of agents to forecast the likelihood of future events. More technically, the previous definition can be rephrased saying that uncertainty is the conditional volatility of a disturbance that is unforeseeable from the perspective of agents.

The study of uncertainty impact on the economy has become popular since the last financial crisis, analyzed as a potential factor responsible for the magnitude and duration of the Great Recession. In 2011, Standard & Poor's even declared that political uncertainty was one of the key reasons that had led them to downgrade the US Treasury debt.

2.1.2 Uncertainty and Risk

Despite being often used as a synonym for risk, as it similarly concerns doubts about the future, uncertainty has a distinct meaning according to Knight (1921). Although both risk and uncertainty refer to a condition in which the future developments are unknown, the notion of risk requires the knowledge of the distribution of probabilities for the outcomes (i.e. risk is a measurable probability involving future events). Instead, the definition of uncertainty indicates that the set of circumstances cannot be matched with a set of probabilities. An example of risk is a game of chance - like a cards game - where the color of the next card in the deck is unknown, but the probability distribution of the different possible outcomes is known. On the other hand, an example of a purely uncertain event is the outcome of US Presidential Elections in 2024, as today it is impossible to form a meaningful view on the probability associated with each of the potential candidates at that point in time.

The difference is even more evident when it comes to decision making. It is believed that agents facing risk typically assign a utility level to each of the outcomes, weight these utilities with the probabilities that the outcome will occur, and then maximize their expected utility (Resnik, 1987). Instead, decision making under uncertainty is more complicated, and many different approaches have been proposed over the years (e.g. Resnik, 1987; Hansson, 1996). Most approaches focus on avoiding the worst-case scenarios or minimizing the lost-opportunity regret. Others instead try to reconcile the decision making under uncertainty to decision making under risk through a subjective assumption, assigning for example equal probabilities to all the outcomes.

Uncertainty is often the more appropriate definition when dealing with large and complex systems (e.g. the economy), where many unpredictable interactions build one onto another, resulting in the impossibility to assign a probability set to the possible outcomes.

2.1.3 Measures of Uncertainty

Uncertainty is a non-observable - and therefore non-measurable - concept (Bloom, 2013). This is the case because it is a psychological, more or less conscious feature, buried in eco-

economic agents minds. Additionally, it is very broad, general and difficult to precisely define, because its origins can be found either in macroeconomics (e.g. cycle and policy shocks), microeconomics (e.g. household, firm expectations and decisions) or non-economic matters (e.g. natural disasters, terrorism).

Indeed, literature regarding the measurement of uncertainty is young. Several proxies have been used, the most popular being volatility of market or macroeconomic indices, mentions of “uncertainty” in the news, degree of disagreement between forecasters of various variables, and firms factor productivity shock dispersion. These proxies should more or less reflect the degree of uncertainty in the minds of market participants, economic agents in general (when considering macro aggregates), press, and professional analysts - offering a quite comprehensive picture.

However, Jurado, Ludvigson and Ng (2015) argue that these proxies are not accurate, despite having the advantage of being directly measurable. They believe that they are for a big part driven by factors different from pure macro uncertainty, they are not representative of different realizations of uncertainty and they wrongly attribute predictable patterns to uncertainty fluctuations. They indeed argue that pure macro uncertainty spikes are less common and more persistent than what is shown by these proxies.

2.1.4 The Time-Varying Counter-cyclical Nature of Uncertainty

The inability of agents to assign a set of probabilities to the different states of the world appears to be time-varying and counter-cyclical, affected by economic and political shocks (or by the prolonged absence of them) and by the status of the economic cycle.

It also varies across different countries, with developing countries displaying on average more uncertainty than developed ones. This seems to be the case due to a more concentrated industrial structure, a reliance to more volatile industrial input/output (e.g. commodities) and a less stable and effective political system⁵ as discussed in the World Bank’s 2013 Development Report and in Koren and Tenereyo (2007).

As a rule of thumb, it has been observed that major shocks increase uncertainty by

⁵More exposed to coups, wars, natural disasters and less able to respond with effective fiscal or monetary policy.

100% to 200% (Bloom, 2006), recessions increase it by 50% to 100% (Schwert, 1989), and uncertainty is about one third higher in developing countries (Bloom, 2013).

Movements in uncertainty are usually asymmetrical. When a shock strikes, agents previous beliefs on the probability distribution of future outcomes stop being valid. Since information on the new state of the world flows with finite speed, and agents need time to process it, uncertainty usually moves upward in jumps. Afterwards, in absence of new shocks, as information flows and agents process it, uncertainty slowly diminishes, displaying a gradual downward movement.

Counter-cyclicality As Bloom (2009, 2013) summarizes, every known measure or proxy of uncertainty is higher during recessions. For example, the VIX is on average 58% higher during recessions, and only a minor part of this increment can be explained by the leverage effect (Schwert, 1989) or by fluctuations in individual risk-aversion. Indeed, Bekaert, Hoerova and Lo Duca (2013) confirm that VIX movements are strictly linked to uncertainty variations. A similar behavior is mirrored by most of financial prices and macroeconomic variables like industrial production, GDP or consumption (Nakamura, Sergeyev and Steinsson, 2012). Results hold even when considering non-market proxies like disagreement among forecasters (Bachmann, Elstner and Sims, 2010) or frequency of articles in major newspapers related to uncertainty (Baker, Bloom and Davis, 2012) and presence of the word “uncertainty” in central bank major releases (e.g. Federal Reserve’s Beige Book). Moreover, the average difference between actual and expected values of macro indicators is 20% higher for the ones released during recessions (Scotti, 2013). Similar findings are reported when considering the size of the forecast error of major macroeconomic models as shown by Jurado, Ludvigson and Ng (2015).

These results hold also when moving the focus from macro aggregates to micro variables (e.g. income, wages) for both corporates (e.g. Campbell et al, 2001; Kehrig, 2011) and households (e.g. Meghir and Pistaferri, 2004; Heathcote, Perri and Violante, 2009; Storesletten, Telmer and Yaron, 2004; Guvenen, Ozkan and Song, 2013).

Results are consistently valid across many different countries (Bloom, 2013). The counter-cyclical nature of uncertainty can be therefore classified as a fractal (i.e. contem-

poraneously valid at macro and micro level) global phenomenon.

Causality The correlation between recessions and uncertainty, despite being extensively proved, has not straightforward causality links.

First of all, almost all the shocks that cause uncertainty spikes are also bad news from a macroeconomic point of view and vice-versa (Bloom, 2009). Even though uncertainty being a *vox media*, it is usually the case that the consequences of good news (e.g. technological outbreaks, political crisis resolutions) are factored in more gradually, as individual risk aversion translates in a conservative approach to optimism in good times. The most intuitive characterization of the phenomenon then suggests that bad news co-cause both recessions and uncertainty spikes, with uncertainty having a subsequent second order effect in worsening the recession. For example, during the Great Recession (2008), it is believed that uncertainty had a role in increasing the severity of the contraction.

Bloom et al. (2014) develop a dynamic stochastic general equilibrium model (based on the standard friction-less real business cycle model) able to fully justify GDP drops and rebounds of 3% driven by reasonably calibrated uncertainty shocks. They also show that, since uncertainty increases caution at firm level and increases volatility of future income, it changes how the economy responds to policy. In facts, higher uncertainty is usually coupled with a diminished effect of government policies in the short run, and an increased effect in the long run.

However, there is also evidence that uncertainty tends to endogenously increase during recessions, together with micro and macro volatilities brought by the downturn. Indeed, Van Nieuwerburgh and Veldkamp (2006), Fajgelbaum et al. (2012) argue that good times are coupled with higher trading volumes and a resulting higher production of information (and thus lower uncertainty), while - during a recession - the information generation and circulation slows down significantly as a consequence of dimmed activity. Another explanation is the one proposed by Pastor (2012): he indicates that, during recessions, policy makers play around with policies more frequently and substantially, as they try to fix problems with experimental approaches. Instead, during expansion times, policy makers usually adopt a less intrusive approach, as they are more comfortable with

the *status quo*. When looking at firms, according to Bachman and Moscarini (2011) and D’Erasmus and Boedo (2011), uncertainty is correlated with a more experimental stance and aggressiveness on R&D, as companies try to reinvent themselves. This micro-uncertainty is then transmitted to macro variables.

Orlik and Veldkamp (2014) find an additional factor in the difficulty that individuals experience when they try to model and form expectations during recessions, as recessionary quarters are far less common than expansionary quarters in history, and most of industry standard models and procedures have been built and fine-tuned under positive growth assumptions - and cannot always be reliably applied when these assumptions fall.

2.2 The Impact of Uncertainty

2.2.1 Business and Investment Activities

In general, literature has found that uncertainty has a short run negative effect on output in aggregate or disaggregate form⁶ via different channels. There is instead some ambiguity regarding the effect of uncertainty on R&D spending, as some companies embrace innovation when facing a more uncertain future, in line with option theory⁷. This suggests caution in assessing the long-run effect of uncertainty on growth.

Ramey and Ramey (1995), in the reference cross-country study on the matter, find a clear negative correlation between volatility and growth, showing that a 1-sigma increase in volatility is on average linked to a 0.5% fall in annualized growth. Since 1995, their results have been corroborated by many others, among whom Engle, Ghysels and Sohn (2008) with more sophisticated statistics, and Baker and Bloom (2011) with political shocks and natural disaster as instrumental variables. The effect is significant and relevant also when considering disaggregated macro output measures like consumer spending (Romer, 1990), investment and hiring (Bloom, 2009), and trade (Handley and Limao, 2012; Novy and Taylor, 2012); or micro (firm-level) variables like investment (Leahy and

⁶Disaggregate form meaning the decomposition of the effect on investment, consumption, trade, employment.

⁷More uncertainty increases the value of a growth option on a future business development, with R&D investments representing the upfront price of the option.

Whited, 1996, Guiso and Parigi, 1999), hiring and advertising (Stein and Stone, 2012). In the same study, however, Stein and Stone find that uncertainty has a positive effect on R&D, confirming Bloom's (2007) argument. Additionally, Bloom (2007) reveals that uncertainty might reduce the responsiveness of R&D to business conditions, while increasing its persistence. He also shows that the marginal effect of uncertainty on R&D is negative for firms that are increasing their R&D, while it is positive for firms that are cutting R&D.

Finally, Bloom et al. (2014) use Census micro-data and confirm that uncertainty is strongly counter-cyclical also at industry-level.

Real Options Channel Business decisions characterized by a high adjustment cost (i.e. the cost of reversing the action), the possibility to wait⁸, and with a direct impact on next periods profitability - like investment and full-time hiring decisions - can be easily reconciled to a set of real options (e.g. Bernanke, 1983; Brennan and Schwartz, 1985; McDonald and Siegel, 1986; Dixit and Pindyck, 1994). For example, a real estate development company, owning a lot of land in Canary Wharf, London's financial center, has now the option to delay the construction of a new office tower until the role of London as a financial hub for Europe will be clarified. Or another example could be a non-British household living in London that decides to delay the purchase of a new house in central London, until the negotiation with EU will be definitive. Evidently, the option-value of the delay is higher during uncertain periods. As Pastor (2013) shows and Gulen and Ion (2016) confirm, this impact of uncertainty is proportional to the degree of investment irreversibility and financial constraints.

In fact, literature (e.g. Bloom, Bond and Van Reenen, 2006) shows that uncertainty clearly reduces the levels of investment and hiring via a delay effect⁹, as well as, the sensitivity of investment to business conditions via a caution effect¹⁰. For example, they show that the impact of a 1% fall in interest rates during high-uncertainty periods increments investments on average by 2.5%, as opposed to a 10% rise during low-uncertainty peri-

⁸Applicable only when there is not a race to market.

⁹ $\partial I / \partial \sigma$: the first order impact of uncertainty on investment and hiring.

¹⁰ $\partial^2 I / \partial \sigma \partial A$ with A being an index of demand conditions.

ods. This phenomenon is taken into much consideration by policy makers when planning counter-cyclical measures, as the spike in uncertainty that is usually joint with recessions makes fiscal and monetary policies much less effective. This indicates that the response to such a shock should also include a second-moment policy in order to stabilize risk and reduce uncertainty¹¹. More precisely, Gulen and Ion (2016) find that two thirds of the 32% fall in corporate investments during the Great Recessions can be attributed to policy-related uncertainty.

The reduction of firm responsiveness has an effect also on productivity (Bloom et al., 2013). When uncertainty is high, productive firms do not expand fast enough and less-productive ones do not contract fast enough, slowing down the reallocation of resources process and productivity growth, making productivity pro-cyclical (King and Rebelo, 1999). This is a different interpretation with respect to traditional real business cycles models like the one of Kydland and Prescott (1982), because the fall in productivity is not anymore the shock itself, but just the implication of an uncertainty shock.

Analogous mechanisms apply to households decisions when purchasing durable goods or housing subject to the same conditions (Carrol and Dunn, 1997), with also a similar effect on elasticity to economic conditions (Foote, Hurst and Leahy, 2000; Bertola, Guiso and Pistaferri, 2005). This increases the overall effect of uncertainty on GDP.

As Pastor (2013) points out, it is possible to instrumentally check these findings, by studying investments in national election years. Indeed, corporates on average reduce irreversible investments by 5% during election years.

Risk Premium Channel It is a foundation notion of modern finance that an increase in uncertainty is associated with an increase in the premium investors require in order to be compensated for the additional risk borne (e.g. Markowitz, 1952; Tobin, 1958; Sharpe, 1964). Since idiosyncratic risk can be diversified away, the financing costs should be only impacted by the systemic uncertainty. As such, an increase in macro uncertainty raises the cost of capital, consequently reducing growth via diminished investments and consumption.

¹¹The recent rise in policy communication and forward guidance is heavily grounded also on this theoretical background.

In parallel, since uncertainty widens the distribution of potential future outcomes, it also increases the probability of default. A lender, being interested only in the left tail of future outcomes distribution (a loan is a fixed income instrument), will charge a higher cost of debt the higher the level of uncertainty, harming growth (Arellano, Bai and Kehoe, 2010; Christiano, Motto and Rostagno, 2010; and Gilchrist, Sims and Zakrasjek, 2014).

Additionally, Ilut and Schneider (2011) study the confidence effect of uncertainty in models in which the state of the world is so uncertain that agents behave as if the worst case scenario will materialize (i.e. ambiguity aversion), being incapacitated to form a probability distribution (i.e. the *strictu sensu* definition of uncertainty). This pessimism naturally results in a cut to investment and hiring¹².

Pastor and Veronesi (2011) develop a theoretical general equilibrium model that allows them to analyze the impact of uncertainty on stock prices. They argue that an increase in policy uncertainty should be coupled with an increase in the volatility and cross-correlation of stock prices (especially during recessions). They also postulate that, in fact, risk premia implied by market stock price would rise when uncertainty increases, and the average size of the premium would be bigger during recessions. Their intuition is that uncertainty should be more powerful during recessions because adverse macroeconomic conditions are precisely the times in which the policy-makers are more likely to change policy. They empirically prove both their hypotheses using US data.

Kelly, Pastor and Veronesi (2014) study the pricing of political uncertainty via a theoretical model of government policy choice derived from Pastor and Veronesi (2013). Then, they empirically analyze the equity option market. They find that options that provide protection against isolated and known in advance political events (i.e. global summits, national elections) are on average more expensive as predicted by the model. This premium is higher the weaker the economy is and the more pronounced uncertainty is. Therefore, they conclude that political uncertainty is priced into the option market. They also document a spillover effect across countries.

¹²The opposite result is observed in over-optimistic environments (sometimes true in the CEO related literature, e.g. Malmendier and Tate, 2005).

Precautionary Savings Channel As shown by Bansal and Yaron (2004), when households face higher uncertainty, savings increase and consumption falls. In small open economies, a substantial part of the increased savings go to other countries, so there is not a parallel rise in investment with positive long run effects on growth (Fernandez-Villaverde et al., 2011). On the other hand, this is not necessarily true for big and relatively close economies, as the reduction in consumption is exchanged for increased investments. However, when analyzing the matter with New Keynesian models, the stickiness of prices is such that prices do not react fast enough to the reduction in consumption, and an uncertainty shock results in a fall in both consumption and investment (Leduc and Liu, 2012; Basu and Bundick, 2013). This is particularly the case when policy response is ineffective (e.g. at the zero lower bound, Fernandez-Villaverde et al., 2013).

The personal precautionary reaction to uncertainty translates into corporate precautionary abstinence from investing when the decision makers of the company are extremely non-diversified as they hold most of their human wealth (i.e. the present value of future salaries) and of their financial wealth (i.e. company's stocks and stock options) in the company they run (Panousi and Pananikolaou, 2012).

Growth Options Channel Differently from the real options case (supra), when companies face long times to develop products and go to market (e.g. pharmaceutical companies), with limited R&D sunk costs, they can buy growth call options at a fixed price (the R&D costs). These call options are more valuable when uncertainty is higher, because the downside remains limited (equal to the price of the option) while the unbounded upside distribution gets more attractive. Therefore, an increase in uncertainty can lead to higher investment in R&D, and to a positive effect on growth (Segal, Shaliastovich and Yaron, 2013). Examples of this phenomenon are the 2000 internet bubble, when the development of a website was considered the purchase of a call option on the highly uncertain success of the internet, or the market of oil drilling leases in relation to oil price volatility (Paddock, Siegel and Smith, 1988).

An empirical example: the Great Recession The Great Recession is a recent and useful example of the impulse and propagation effect that uncertainty has on the economic cycle.

Following the housing and financial collapse in 2008, every measure of uncertainty spiked and remained high for various quarters, causing a big (three times the average size) and abnormally persistent (two times the average persistence) uncertainty shock to the global economy. Bloom (2013) estimates via empirical simulations that the uncertainty shock accounted for a third of the US GDP contraction of 2008-2009 (3% out of the 9% drop against trend).

The financial and housing crisis explosion had a first order bad-news effect on both output and uncertainty (co-causation). Uncertainty spiked because the size and extent of the ramifications of the shock were very unclear, as well as the coming response of fiscal and monetary authorities. The surge in uncertainty then hit output as a second moment shock. The recession was therefore induced by a combination of first- and second-moment shocks of abnormal magnitude, similar to what happened in 1929.

Subsequently, the recession induced more uncertainty, due to the aggressiveness and unprecedented nature of the monetary and fiscal responses (Baker, Bloom and Davis, 2012) as well as micro uncertainty about the possibility of ever returning to past levels of growth. After 2010, most of the uncertainty measures reverted to normal levels, except for the Economic Policy Uncertainty¹³ that is still relatively high, due to fiscal and monetary abnormal conditions. This probably had a role in slowing down the recovery.

2.2.2 Financing Activities

When it comes to financing activities, literature is not as complete as in the investment activities case. Results, however, tend to be in line with expectations.

Cao, Duan and Uysal (2013) extend a borrower-lender information asymmetrical model (on the back of Holmstrom and Tirole's famous works) to find that, in highly politically uncertain times, borrowing frictions are higher, resulting in reduced credit

¹³Measure of uncertainty developed by Baker, Bloom and Davis (2012) that reflects the frequency of economic uncertainty related news in newspaper publications.

supply and increased borrowing costs. They argue and then empirically demonstrate that, therefore, firms tend to reduce (or not increase) leverage in order to remain financially flexible, wait longer to issue debt and hold more cash (confirmed also by Gulen and Ion, 2016). They also show that firms with access to public debt markets are less prone to reduce leverage due to uncertainty spikes. In line with their findings, they argue that this impact is stronger on firms with a higher degree of political risk exposure (e.g. defense, energy). They finally show that this effect of political uncertainty on leverage is different in nature from the above mentioned effect on investment decisions.

2.3 The Determinants of Corporate Finance Transaction Waves

Academics and industry practitioners have observed that corporate finance transactions tend to happen in waves.

In this section, we discuss the individual streams of research concerning mergers, equity capital markets and debt capital markets, respectively. The widest academic production concerns merger waves, while debt capital markets are the least explored. We conclude the review with an analysis of corporate finance transactions as a whole unique phenomenon.

2.3.1 Merger Waves

Within this category, literature on the topic identifies some elements which are common to all merger waves in history (Ceddaha, 2007; Depamphilis, 2010): sustained economic growth, low interest rates and increase in the capital market activity (Andrade et al., 2001). Moreover, waves often originate during periods of economic recovery, when the re-engineering made necessary by the recession occurs in the form of M&A.

Academics also agree in the number and timing of the M&A waves that occurred in history. They point out six of them (see Table 1 for a timeline of merger waves; see Table 8 for a comprehensive list of their determinants).

Start Year	End Year	Definition	Notes
1893	1904	Horizontal Mergers	Involved major mining and manufacturing industries; involved 15% of all manufacturing assets and workers
1916	1929	Increasing Concentration	Consequence of the entry of US into WWI, it ended with the 1929 stock market crash and the Clayton Antitrust Act
1965	1969	The Conglomerate Era	Emergence of financial engineering and conglomeration; the longest period of uninterrupted growth in US history resulted in record P/E ratios
1981	1989	Hostile Takeovers (the Rentrenchment Era)	Breakup of major conglomerates; hostile takeovers and LBOs as primary acquisition strategies
1992	2000	The Age of Strategic Mega Mergers	The wave ends with the burst of the millennium bubble and corporate scandals (e.g. Enron)
2003	2007	The Rebirth of Leverage	Highly-leveraged buy-outs, PE investments and proliferation of complex collateralized securities; most of the financing in the form of syndicated debt

Table 1: Timeline of Merger Waves since 1893 - waves definitions are reported as from Varizani (2015)

Literature on merger waves begins with Nelson (1959): he is the first academic to point out that mergers are strongly concentrated in time and cluster during periods of high stock market valuations. The determinants of such waves, however, start being investigated only a decade later: focusing on the merger rate¹⁴ as his main variable of interest, Gort (1969) observes systematic variations in the discrepancies of valuation between owners and non-owners of firms. The author states that industry shocks – or economic disturbances, such as changes in the technological or regulatory environment –

¹⁴Merger rate is “the ratio of number of acquisitions to the population of business firms in the relevant sector – that is, the maximum number of firms that can be acquired” (Gort, 1969).

ultimately lead to several sequential mergers.

After Gort, valuation remains the focus of behavioral corporate finance, which sees corporate policies – such as debt and equity issuance, share repurchases, dividends and investment – as a response to market mispricing. More specifically, it associates the occurrence of merger waves to discrepancies in company valuations.

The main publications within the behavioral corporate finance field belong to Shleifer and Vishny (2003), Rhodes-Kropf and Viswanathan (2004) and Gugler et al. (2012).

Shleifer's and Vishny's (2003) model of stock market acquisitions suggests that, when the managers of the acquiring company are aware of the company's overvaluation, they decide to exchange shares for tangible assets; through a merger or an acquisition, they thus protect company's shareholders before the market can correct the shares rate. It has to be specified that, while the authors do not believe in full efficiency of capital markets, they assume mergers cannot be wealth-destroying: this assumption is released only in Gugler's work (2012), which we discuss below.

Shleifer and Vishny are placed within a broader school of thought: data about merger activity, indeed, unanimously suggest that periods of stock merger activity are correlated with high market valuations (Andrade et al., 2001; Verter, 2002). This is often explained by the fact that overvalued bidders are willing to use stock. Rhodes-Kropf and Viswanathan (2004), while trying to go beyond this simplistic and incomplete view of the phenomenon, get to confirm the key impact of valuation on mergers. A correlation between stock merger activity and market valuation, in fact, does exist. Moreover, the detected mis-valuations seem to be enough to cause a wave by themselves: even without deregulation, innovation and corporate governance issues – identified by the authors as traditional reasons for a merger – waves can occur.

Both the works by Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) belong to the overvaluation theory of merger waves. Indeed, they predict that mergers will occur only for those firm which are overvalued.

Gugler et al. (2012), when discussing their managerial theory of mergers, give a valuable and complete view of the phenomenon, while allowing for the existence of wealth-destroying mergers: this is a point of differentiation with respect to Shleifer and Vishny

(2003). Their comprehensive view also includes a more prominent role of optimism: the authors consider both firm-specific measure of market optimism – firm overvaluation, as in the overvaluation theory – and more general market measures – aggregate P/E and the spread between the federal funds rate and the commercial and industrial loan rate (i.e. the interest rate paid by blue chip firms to borrow money). Moreover, Gugler’s theory can account for mergers which use all means of finance (while overvaluation concerns shares-only deals).

Gugler et al. (2012) argue that understanding the psychology of both managers and financial markets is necessary to understand merger waves. The authors relax the assumption of a full capital market efficiency, allowing the possibility that markets can be gripped by periods of over-optimism or pessimism. Results show that the key measures of optimism – P/E, interest rate spread and overvaluation – are significant determinants of mergers: these findings represent a comprehensive summary of behavioral theories of mergers and include those reached by the supporters of the overvaluation hypothesis.

In opposition to behavioral economics, the neoclassical theory tries to explain merger waves without allowing for market inefficiency. Neoclassical academics mainly perform sector- and country-level analyses and assume profit-maximizing managers, wealth-creating mergers and efficient capital markets. In general, they explain merger waves as resulting from a combination of economic, technological and regulatory shocks in a certain sector: shocks make operations become profitable and favorable economic conditions lower the cost of financing, thus leading to a merger wave in that specific industry.

Among neoclassical authors: Jovanovic and Rousseau (2002) represent a milestone in traditional neoclassical theory; Harford (2005) proposes an augmented – and more solid – version of their model; and Rodrigues (2013) interestingly introduces the concept of merging costs.

According to Jovanovic and Rousseau (2002), who extend the Tobin’s Q-theory of investment to mergers, waves tend to appear during capital markets booms. The idea that mergers represent asset relocation suggests that these operations should occur when there are important technological changes, and disappear when the asset relocation is complete.

Models like Jovanovic's are often criticized, because they fall short in explaining the relatively high market values of acquiring firms during a wave (Marcum et al., 2015). Harford (2005) addresses this apparent weakness, stating that technological shocks alone are not enough: a necessary condition for them to trigger a merger wave is represented by the existence of enough liquidity capital to allow asset relocation.

Finally, Rodrigues (2013) develops a Cournot competition model of merger waves. He explains how the occurrence of industry merger waves is determined by the relationship between the synergy opportunities offered by mergers (private gains) and the possibility to free-ride other firms' mergers market power effects (public gains). The author finds out that waves are to be expected when two conditions occur: on one hand, the private gains generated by the merger are not too low (when compared to the free-riding public gains generated by other parties merging); on the other hand, the industries are not so sensitive to the number of insiders that a single large merger of multiple firms overcomes the succession of small mergers¹⁵. Moreover, Rodrigues also identifies merging costs – increasing in the number of merging partners – as an additional determinant of waves: these costs counter the incentive for large mergers involving multiple firms, in favor of smaller-size deals.

Within this section about M&A waves, we observe two opposing schools of thought: behavioral corporate finance, on one hand, does not assume the efficiency of capital markets and attributes a central role to companies' overvaluation and investor sentiment; on the other hand, neoclassical theory emphasizes the role of technological shocks and – in its augmented version – of liquidity capital. While these two theories have not found a synthesis at the M&A level, Rau and Stouraitis (2011) manage to propose a view on corporate finance deals that combines them both.

A final consideration is to be made, given that all the above-discussed works study a sample of public firms only. Maksimovic et al. (2013) observe that public companies' engagement as buyers and sellers of assets in merger waves is affected more by credit spreads and aggregate market valuation than private firms'. Furthermore, Netter et al.

¹⁵If the private merger gains are sufficiently large and increasing in the number of insiders to the merger, the equilibrium is a single large merger to monopoly.

(2011) show that the pattern of merger waves is much smoother, when they include small deals and private acquirers too.

2.3.2 Equity Capital Markets Waves

For what concerns equity capital markets, most of the works address the clustering of initial public offerings (Pastor and Veronesi, 2005; He, 2007); only a few of them try to describe ECM deals as a whole category (Rau and Stouraitis, 2011).

Clustering of initial public offerings starts being documented by Ibbotson and Jaffe (1975). The causes behind the phenomenon, however, are less clear. At a general level, non-financial reasons seem to play a minor role in the clustering of IPOs (De Jong and Legierse, 2013). Academics, indeed, identify several finance-related factors: GDP growth (Rau and Stouraitis, 2011) and level of interest rates (Lowry, 2003); overall market conditions (Helwege, 2004; Batnini and Hammami, 2015) and volatility of returns (Choe, 1993, Pastor and Veronesi, 2005); market sentiment (Rajan, 1997); specific industry conditions (Pagano, 1998); level of equity valuation (Lerner, 1994; Banerjee, 2012); necessity to finance innovation (Pastor and Veronesi, 2005).

Out of this wide production, the main works come from Lowry (2003) and Pastor and Veronesi (2005). In addition to their academic relevance, these works are particularly interesting for the purpose of our paper, since they explicitly account for uncertainty.

We also include the findings of Alti (2005), He (2007) Chemmanur and He (2011) and De Jong and Legierse (2013), given their novel – although narrower – contributions to the study of this topic.

Lowry first studies IPO waves in 2002, showing that there are three main determinants behind fluctuations in IPO volume: changes in private firms' aggregate demand for capital, changes in the adverse selection costs of issuing equity and variation in investor optimism. The following year (2003), noticing that the observed variation in IPO volumes is far in excess of the variation in capital expenditures, the author tests three possible explanations¹⁶ for the phenomenon. Results show that investor sentiment is not the only

¹⁶The author tests three different explanations: IPO volumes vary with business cycles; IPO volume fluctuations are driven by changes in investor optimism; the lower numbers of IPOs during periods of high uncertainty potentially reflect a lemons problem.

factor behind IPO waves, as suggested by previous research: firms' demands for capital is also a key determinant – both statistically and economically; adverse-selection costs, instead, are only statistically – but not economically – significant.

In addition to this, Lowry's work uses uncertainty as a proxy for information asymmetry. Since information asymmetry is unobservable, Lowry uses the dispersion of abnormal returns around public firms' earnings announcements and the dispersion of analyst forecasts on public firms' earnings as measures of uncertainty. Both these measures focus on earnings, and they should thus reflect uncertainty about assets in place, which potentially prevents firms from issuing equity, as shown by Myers and Majluf (1984).

“Rational IPO waves”¹⁷ (Pastor and Veronesi, 2005), which opposes the overvaluation hypothesis, also explicitly accounts for uncertainty¹⁸ when explaining the waves phenomenon. Studying a sample of firms over the period 1960-2002, the authors find that IPO waves tend to be preceded by high market returns and followed by low market returns; in fact, when market conditions worsen, stock prices drop and the volume of deals decline, because private firms decide to wait for more favorable conditions before going public.

Previous works by Pastor and Veronesi (2003) adopt different measures for uncertainty. Being not possible to observe the key variables of interest – the equity premium and prior uncertainty about average profitability – the authors build two proxies: NEWVOL, which compares the return volatilities of newly IPO-ed firms to the long-lived firms; and NEWMB, which compares the M/B¹⁹ ratios of IPOs to the long-lived firms.

Alongside with the publications discussed above, a few works are noteworthy, thanks to the elements of novelty they introduce: Alti (2005) describes the relationship between information spillovers and IPO waves; He (2007) investigates how investment banks influence asymmetric information and, consequently, hot markets (Ritter, 1984); Chemmanur and He (2011) fill a gap in literature by modeling product market competition in relation to IPO waves; to conclude, De Jong and Legierse (2013) shed some light on the role of

¹⁷As opposed to those “irrational” IPO waves, triggered by an overvalued market.

¹⁸Pastor and Veronesi model a time-varying “prior uncertainty”, which can be defined as the “prior uncertainty about the post-IPO average profitability in excess of market profitability” (Pastor and Veronesi, 2005).

¹⁹M/B: ratio of market equity to book equity (Pastor and Veronesi, 2003).

opportunistic behavior of firms.

Alti (2005), focusing on stock valuation in the IPO market, gives information spillovers²⁰ across IPOs a central role in the creation of IPO waves: indeed, information spillovers from pioneers' IPOs help increase investors' confidence on common valuation factors, and thus make going public less costly for the followers. The authors describe a jump in IPO volume in response to high offer prices: high offer price realizations for pioneers better reflect investors' information, facilitate a more powerful spillover effect and thus trigger a larger number of subsequent IPOs.

The role of information is not new within literature about corporate finance waves: Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) already explore the reduction in asymmetric information as a trigger for merger waves.

When performing a comprehensive analysis of literature on IPO waves, He (2007) proposes the role of investment banks and their impact on asymmetric information as a key determinant: during "hot" IPO markets, indeed, the information produced by investment banks makes it possible for investors to accept companies that would have been excluded without information production. This happens because the information provided by banks improves quantity and quality of data around going-public firms, allowing *ex-ante* low quality firms to be analyzed with sufficient confidence by investors and to go public at an appropriate price. At the same time, the information produced has a positive effect also on the *ex-post* IPO firms, driving up first-day returns on the secondary market. This mechanism is able to explain a synchronization effect between IPO volumes and first-day returns.

Identifying a gap in literature, Chemmanur and He (2011) develop a model to study the effect of product market competition on IPO waves. They find out that IPO waves might occur in equilibrium even in those industries which do not experience a productivity shock, or for those firms which hold sufficient internal capital: the driver, indeed, is the possibility of competitors on the product markets going public.

Finally, De Jong and Legierse (2013) find that, alongside with recurring economic

²⁰A stream of research focuses on information spillovers as the main driver of the hot market phenomenon. The idea is that "information generated in valuing a set of pioneers makes the valuation of followers easier and hence triggers more IPOs" (Alti, 2005).

determinants, IPO clustering is also explained by firms' opportunistic behavior. Companies, indeed, use a window of opportunity to receive the highest-possible payoff: most likely, when valuations are high, sentiment among investors is positive, volatility of returns is low and expectations are optimistic.

Within literature on ECM waves, some authors (Lowry, 2002 and 2003; Pastor and Veronesi, 2003 and 2005) explicitly account for uncertainty as a significant determinant. Alongside with it, academics identify other factors: overall market conditions, volatility of returns, investor sentiment and information spillovers.

2.3.3 Debt Capital Markets Waves

Debt issues also happen in waves, as documented by Rau and Stouraitis (2011). Literature on the topic is much narrower than the production about M&A or equity issues and focuses mainly on initial debt public offerings.

Cai et al. (2013) conduct a large study on debt initial public offerings (DIPOs) over a 41-year period (1970-2010). At a general level, they find that DIPO volume is significantly linked to aggregate book-to-market ratio, lagged equity IPO (EIPO) volume, stock return volatility, yield spread and term spread: this suggests that both investor sentiment and capital market conditions play a key role in explaining debt initial public offerings. Among DIPOs, speculative-grade²¹ issues appear to be synchronized with business cycles, while investment-grade issues are characterized by a steady or counter-cyclical pattern.

The authors go a step further and compare DIPOs – both high-yield and investment-grade – to EIPOs, seen as competing financing alternatives for a firm. There is evidence of a dynamic relation between EIPO waves and DIPO waves, with EIPOs leading DIPOs. Results also seem to support the empirical evidence on the similarity between high-yield debt and equity (Blume et al., 1991; Shane, 1993).

²¹The authors refer to the Standard & Poor's Bond Ratings. Therefore, speculative-grade bonds have either BB, B or CCC ratings, while investment-grade bonds can have BBB, A, AA or AAA ratings. The studied sample is evenly distributed among speculative-grade and investment-grade.

2.3.4 Corporate Finance Waves as a Whole

Only recently, academics started considering corporate finance deals and their clustering in time as one, whole phenomenon. The study published by Rau and Stouraitis (2011) is the first of this kind. The authors conduct a comprehensive analysis of the “Patterns in the timing of corporate event waves”, covering five types²² of corporate finance deals over the 1980-2004 period; each deal differs in the way it involves either financing or investment decisions. The study provides us with a complete, cross-deal timeline of corporate waves, which holds over separate decades and across industries: corporate waves start with new issue waves – with seasoned equity offerings preceding IPO waves; then, merger waves follow; finally, repurchase waves occur.

While academic publications about corporate finance deals are often divided between neoclassical and behavioral theories, this work ideally represents a synthesis of the two: indeed, results seem consistent with both theories, and there are distinct periods when one or the other prevails.

²²The authors cover: new stock issues; seasoned equity issues; stock-financed acquisitions; cash-financed acquisitions; and stock repurchases.

3 A Measure of Uncertainty: the UIX

In this section, we define an uncertainty index (UIX) we will use in the remaining part of the paper to address our research questions regarding the impact of uncertainty on corporate finance transactions. We discuss its construction, main features and interpretation.

3.1 Data

To build our index, we choose to analyze the implied and realized volatilities of the stock market and currency market, the realized volatility of the 10-year reference interest rates, and the Economic Policy Uncertainty Index (EPU) built by Baker, Bloom and Davis (2012).

Our choice is motivated by data availability at monthly frequency for all the eight countries included in the panel. As briefly noted in literature review, additional possible series tend to be highly correlated with the selected ones and display very similar patterns. Moreover, we decide to give the market series a prominent role because they tend to be more reliable and precise at monthly frequency. Indeed, under generic hypothesis of market efficiency, they should capture in real time all the available (lack of) information market participants deal with.

We choose to include the EPU measure in order to add a qualitative dimension to our index. This is particularly important in this period because market variables are endogenously affected by central banks decisions, while non-market based indicators can give a different view on the real uncertainty agents face. Indeed, over the last few years, there has been a divergence between market variables, which are back to pre-2008 levels, and the EPU, which has stayed well above the Great Moderation levels.

3.1.1 Economic Policy Uncertainty (EPU) Index

Baker, Bloom and Davis (2012) propose a measure of economic policy uncertainty, based on newspaper mentions of some selected keywords. For every country, they count the frequency of articles containing the triple: (i) "uncertain or uncertainty"; (ii) "economy or economics"; (iii) one or more terms out of a set of policy words (e.g. for the US:

“congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation”, “White House”) in the leading domestic newspapers. They regularly update the measure for 15 countries.

Limitations regarding reliability and potential biases due to the newspaper-based nature of this index are extensively addressed by the authors in the original and subsequent publications. They demonstrate a strong relationship of this measure with other commonly used uncertainty proxies. They also show that the political slant of the newspapers included in the sample does not cause distortions to the uncertainty measures obtained. Finally, they test their automatic articles classification system against a human-produced classification, finding a very strong correlation between the computer and human generated indices (0.86 quarterly, 0.93 annually), with the discrepancy being non correlated with macro variables, or the index itself.

Since inception, this database has been very successful, both in academia and in the financial industry. As a matter of fact, it is now carried by many major data providers (e.g. Bloomberg, FRED, Reuters) in order to serve a growing user base, receiving in this way some sort of market validation.

The main advantage of such a measure is the fact that newspapers have been available in more or less the same form in many countries and for many decades. Newspapers can be in fact considered a long-term ubiquitous qualitative measure of contemporary perceptions.

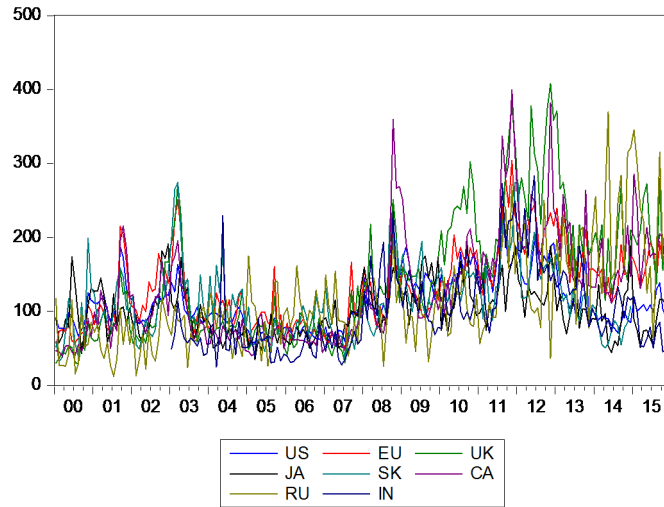


Figure 1: Economic Policy Uncertainty Index for the 8 Panel Countries

Looking at Figure 1, showing the EPU over time for the 8 countries included in the panel, we notice that: (i) the series are very noisy and volatile; (ii) there are visible spikes in correspondence of major shocks (e.g. 9/11, Lehman); (iii) after 2008, the series can be characterized by both a higher first and second central moment.

We retrieve monthly data from the official Economic Policy Uncertainty website²³.

United States, Europe, United Kingdom, Japan, Canada, Russia offer the full Jan-00 to Dec-15 series. South Korea is limited at Dec-14; India starts on Jan-03.

Descriptive statistics of the sample are attached in the Appendix (Table 9-10).

3.1.2 Implied Volatilities

Widely adopted as the best real-time indicator of uncertainty as perceived by market participants, implied volatility is a mathematical function of option prices. In summary, it is the value of the volatility of the option's underlying instrument that would return a price equal to the market price of the option, when used as input in an option pricing model.

²³<http://www.policyuncertainty.com/>

The key input for its computation is the price of the option; it thus requires the existence of options publicly traded on the relevant underlying.

In our index, we include the implied volatility of the main domestic stock market index as measured via the CBOE VIX methodology, and the implied volatility of the domestic currency.

Stock Market Implied Volatility The implied volatility of the domestic stock market is directly available by taking daily closures of CBOE Volatility Index (VIX) or equivalently calculated traded indices²⁴ for other countries. Indeed, nowadays the majority of the key equity indices have also an actively traded volatility index. Details on the name of the selected series are available in Table 12.

We retrieve daily closures from Bloomberg. We take the simple average of the daily data to get to our monthly frequency.

United States, United Kingdom, European Union, Japan offer the full Jan-00 to Dec-15 series. Canada starts on Dec-02, South Korea on Jan-03, Russia on Jan-06, India on Nov-07.

Domestic Currency Implied Volatility Calculating the implied volatility of the domestic currency is more difficult, as there is not a summary index already available.

To build a summary index, we first select a set of representative currencies. Based on global trade volumes, free floating nature, availability of traded options on the pairs and independence of the central bank we select seven main currencies: US Dollar (USD), European Euro (EUR), British Pound (GBP), Japanese Yen (JPY), Swiss Franc (CHF), Australian Dollar (AUD), Canadian Dollar (CAD). We then narrow down the set to the pairs that actually had options traded for long enough. Table 13 in the Appendix summarizes the utilized pairs of currencies.

We retrieve from Bloomberg the 1-month daily implied volatility for the currency pairs with publicly traded options during our time-frame.

²⁴VIX is a traded index obtained as the square root of the price of variance, with the price of variance derived as the forward price of a particular strip of index options. The strip of options is made of determined out-of-the-money puts and calls on the index.

We produce a synthetic index by taking the first principal component of the selected pairs implied volatilities, and then calculating the monthly average.

United States, United Kingdom, European Union, Japan, Canada, South Korea offer the full Jan-00 to Dec-15 series. Russia starts on Mar-05, India on Nov-07.

3.1.3 Realized Volatilities

We also include the realized volatilities on the main domestic equity index, the domestic currency and the yield of the domestic 10-year government bond. We use realized volatilities as proxy of uncertainty by exploiting the market efficiency hypothesis; then we consider volatility as an indicator of the degree of difficulty investors face when pricing financial instruments, due to their inability to forecast future values.

Domestic Market Realized Volatility We draw on Bloomberg to obtain the main domestic index daily closure prices for each country and then we calculate the monthly standard deviation of its log returns. Table 11 in the Appendix summarizes the selected indices.

Domestic Currency Realized Volatility Following the same structure used for implied volatilities, we retrieve from Bloomberg the main currency pair daily closure values for each country, we standardize them and then we calculate the monthly standard deviation. Subsequently, we take the first principal component of the standard deviations, to obtain a one-dimensional index.

Table 14 in the Appendix summarizes the selected pairs.

Domestic Rates Realized Volatility We retrieve from Bloomberg the 10-year reference government bond yield for each of the country. We calculate the monthly standard deviation.

3.2 Construction of the Index

In order to summarize these very correlated measures in an unique index, we standardize them and then proceed via a principal components analysis country by country. We take the first principal component as our uncertainty index (UIX).

The first principal component explains on average 59% of the overall variability for each country, as shown in Table 2.

Sub-Set	Proportion Explained
US	0.6533
EU	0.5777
UK	0.5595
JA	0.5493
SK	0.6322
CA	0.5991
RU	0.5417
IN	0.6096
Average	0.5903

Table 2: Proportion of Variability Explained by the First Principal Component

3.3 Features of the UIX

In the following figures, it is possible to appreciate the UIX time series for the eight considered countries, as well as its descriptive statistics.

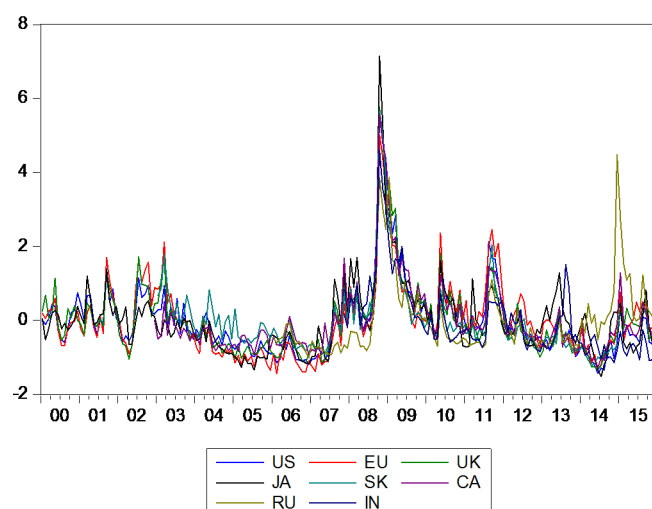


Figure 2: The UIX for the 8 Panel Countries

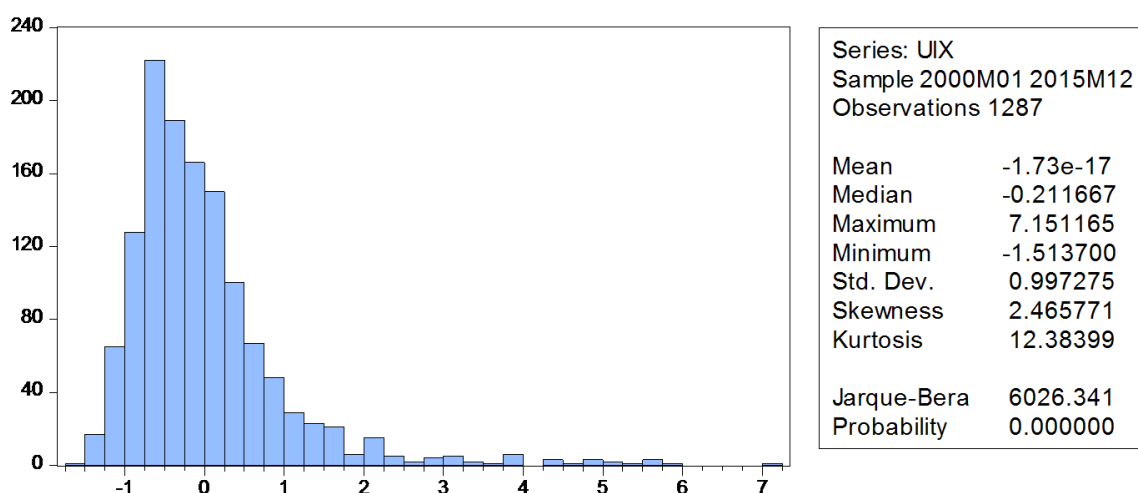


Figure 3: Descriptive Statistics for the UIX

Looking at Figure 2, it is possible to observe how the long term downward trend of the “Great Moderation” met a major break point with the 2008 financial crisis. On that occasion, the entire database peaks and takes some quarters to come down. Afterwards, a higher second central moment - with respect to the first part of the data-set - is visible. The first moment, however, decreases up until the beginning of 2015.

The values of the index can be interpreted in a very intuitive way. The index is locally centered at 0 (it is built separately country-by-country), with 0 meaning average

(i.e. usual) local uncertainty level. When the index goes above 0, it means that uncertainty is higher than the historical regular level for that country, and vice versa. The relative historical high is 7.15, registered in Japan in October 2008 (Lehman). Only 7 other data points are beyond 5, namely the October 2008 record for the US, the European Monetary Union, the UK, South Korea and Canada, and the November 2008 record for Japan and the US. The historical low at -1.51 is again in Japan as of July 2014. Other notable low scores are the February 2006 in the European Monetary Union (-1.44), and the June 2014 in the US (-1.43).

As noted in the previous comments, the first and most important feature of the UIX is the fact that financial uncertainty is mainly a global phenomenon. Indeed, this is confirmed when looking at the cross-country same-period correlations as in the following Table 3.

	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.9445	1.0000						
UK	0.9759	0.9192	1.0000					
JA	0.8992	0.8540	0.9148	1.0000				
SK	0.9613	0.9285	0.9596	0.9045	1.0000			
CA	0.9774	0.9216	0.9710	0.9179	0.9624	1.0000		
RU	0.6913	0.6603	0.7229	0.6869	0.7079	0.7308	1.0000	
IN	0.8743	0.8039	0.8770	0.8344	0.8964	0.8804	0.6247	1.0000

Table 3: Cross-Country Contemporaneous Correlation for the UIX

The second important feature we notice is that UIX is persistent. Indeed, looking at auto-correlations, we see a clear picture, as shown in Table 4 correlogram.



Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.812	0.812	849.54	0.000
		2 0.665	0.020	1421.1	0.000
		3 0.544	-0.004	1803.7	0.000
		4 0.442	-0.009	2056.2	0.000
		5 0.368	0.026	2231.3	0.000
		6 0.320	0.043	2364.0	0.000
		7 0.313	0.106	2491.1	0.000
		8 0.290	-0.019	2600.3	0.000
		9 0.268	0.006	2693.4	0.000
		10 0.230	-0.039	2762.4	0.000
		11 0.211	0.042	2820.1	0.000
		12 0.183	-0.017	2863.5	0.000
		13 0.147	-0.028	2891.8	0.000
		14 0.140	0.047	2917.2	0.000
		15 0.114	-0.048	2934.0	0.000
		16 0.084	-0.036	2943.1	0.000
		17 0.049	-0.032	2946.3	0.000
		18 0.054	0.081	2950.2	0.000
		19 0.065	0.031	2955.7	0.000
		20 0.018	-0.153	2956.1	0.000

Table 4: Auto-Correlation for the UIX

Lastly, by looking at the histogram in Figure 3, the positive and substantial skewness reflects the fact that uncertainty increases in jumps and returns to normal slowly and gradually.

These features are expected - and in a certain way required - for an uncertainty measure. They are all in line with the first section of literature review²⁵ and they resemble patterns visible in the most famous uncertainty index, the VIX. Indeed, correlation between the two is consistently very high, as indicated in Table 5.

²⁵We defer to that section for a thorough explanation of the reasons behind these common and known patterns.

Sub-Set	Correlation
US	0.9364
EU	0.9107
UK	0.9153
JA	0.9236
SK	0.9201
CA	0.9341
RU	0.8106
IN	0.8918
Total	0.9104

Table 5: Correlation between UIX and VIX

4 The Impact of Uncertainty

In this section we investigate if and how the uncertainty index (UIX) developed in section 3 impacts corporate finance transactions. Although financial press and investment banks often attribute to uncertainty the power to disrupt deal activity, the magnitude of this phenomenon is not empirically clear.

In the first subsection we outline the research questions, in the second we describe the data-set, in the third we present the main results, in the fourth we check the robustness of the results. Finally, in the fifth section, we extend the analysis to a quarterly model, including investments and loans at the national economy level as explanatory variables.

4.1 Research Questions

We investigate 7 different subsets of transactions, and we study each of them on two correlated axis: by aggregated monetary value (herein labeled as value or VAL) and by number of deals (herein labeled as volume or VOL).

Corporate Debt Capital Markets (DCMC): *Is the recourse to financing by corporates on the debt capital markets materially negatively impacted by an increase in uncertainty?*

We expect a positive answer to this question, as on the capital demand side, debt financing should mirror literature findings on the dynamics of investments under uncertainty, and an eventual reduction in leveraged deals should reduce the high yield bond issuance. This should be reinforced on the capital supply side, where investors may be less prone to put money into the market when uncertainty is high, sitting on the cash for a period as the value of the optional delay increases with uncertainty.

Core Corporate Debt Capital Markets (DCMCC): *Is the recourse to financing by corporates on the debt capital markets, excluding Mortgage Backed Securities (MBS) and Asset Backed Securities (ABS), materially negatively impacted by an increase in uncertainty?*

By removing MBS and ABS from the count, we clean the variable from the overwhelming growth of this sub-market in the first half of the 00s decade, and subsequent bust after Lehman. At the same time, we down-weight financial institutions activity in this market, that otherwise would dwarf the rest of the economy.

Under this specification, we expect similar but cleaner results *vis-à-vis* the first specification on the full DCM spectrum, especially in the US, where ABS market were more developed during the considered time frame.

Government Debt Capital Markets (DCMG): *Is the recourse to financing by government and governmental agencies on the debt capital markets materially negatively impacted by an increase in uncertainty?*

Governments are seldom in the position to time the debt market and they tend not to do that. Additionally, they are usually the best rated creditor in an uncertain period and, as such, they become a popular destination for investors fleeing from more risky assets. Moreover, an expansionary fiscal policy can be implemented in conjunction with an uncertain period, with the government spending financed with debt. Given the negative correlation between the cycle and uncertainty, uncertainty can actually be positively correlated with government spending. This last factor, however, can be very country-specific. Therefore, after controlling for the cycle, we expect uncertainty to have an ambiguous effect on government debt issuance in the panel.

Equity Capital Markets (ECM): *Is the recourse to financing on the equity capital markets materially negatively impacted by an increase in uncertainty?*

Equity Capital Markets, taken as a whole, include IPO, follow-on offers, right issues, and recapitalizations. We expect uncertainty to negatively impact ECM, for the same reasons explained above for DCM. However, recapitalizations and right issues should tend to happen in conjunction with uncertain times and, as such, mitigate the negative relationship, even after controlling for the cycle.

IPOs Only (IPO): *Is the recourse to financing on the equity capital markets - in the form of an Initial Public Offering (IPO) - materially negatively impacted by an*

increase in uncertainty?

By studying IPOs only, we remove follow-on offerings, right issues and recapitalizations from the count, investigating a particular portion of the market which is thought to be very much driven by timing considerations on the capital demand side, and by investor confidence on the capital supply side. We expect a strong negative impact of uncertainty on IPOs, as already suggested by part of literature.

M&A Completed or Pending (MA): *Is the merger and acquisition (M&A) activity materially negatively impacted by an increase in uncertainty?*

It is known that the macroeconomic cycle, as well as market prices, impacts M&A activity. Our investigation on the potential additional impact of uncertainty is expected to lead to a negative coefficient. However, we are aware of at least a couple of features that can limit this phenomenon. During uncertain times we would not be surprised to see divestitures aimed at deleveraging and refocusing on core business, as well as cross-border transactions in line with an objective of geographical risk exposure diversification. Moreover, there is the possibility of opportunistic deals that take advantage of depressed valuations and fire sales.

M&A Withdrawn (MAW): *Are the merger and acquisition (M&A) deals that fail and get withdrawn in any given month materially positively impacted by an increase in uncertainty?*

Even though the data-set is not very representative, as most of the failed M&A happens behind the scenes, it is still interesting to check whether uncertainty has a role in the already-announced M&A transaction that subsequently derail. Another big problem of this series is that it is dependent of number of deals announced, and as such, results are difficult to interpret.

4.2 Data-set

As already mentioned, our panel is described by the following dimensions:

- ◇ Frequency: monthly data

- ◇ Time (16 years): January 2000 to December 2015
- ◇ Cross Section (8 countries): United States (US), Euro Monetary Area (EU), United Kingdom (UK), Japan (JA), South Korea (SK), Canada (CA), Russia (RU), India (IN)
- ◇ Data points: 1,287 (without considering missing data)
- ◇ The panel is unbalanced as missing data are not evenly distributed

4.2.1 Study Variable

The study variable is the UIX as built in Section 3.

As a result of the principal components decomposition, the UIX is already comparable across countries.

4.2.2 Dependent Variables

For each of the seven different transaction specification we refer to the Thomson One database as of April 22, 2016. Every variable is analyzed both in values (`_VAL`) and in volumes (`_VOL`), with values representing the monetary sum of the transaction sizes, and volumes representing the number of unique deals.

Values are converted to local currency²⁶ in order to be consistent with the independent variables specification, and then divided by the domestic Consumer Price Index (CPI) in order to obtain real term variables²⁷.

Both volumes and variables are then log-transformed by using a $\log(x+1)$ transformation²⁸, a common practice used to normalize right-skewed, non negative data containing zeroes (i.e. most of our series).

Finally, to build a homogeneous panel, all dependent variables are standardized country by country. Therefore, for each country, a value of 0 can be interpreted as the

²⁶Thomson One database records values in US Dollars.

²⁷The CPI is retrieved from either the National Statistics Institute or the Central Bank database.

²⁸Box-Cox (1964) extended form transformation with $\lambda_1 = 0$ and $\lambda_2 = 1$.

average activity in each specific transactional field, and any positive (negative) number represents a level of activity a multiple of its standard deviation above (below) the average.

The figures in this section refer to final variables post-transformation, while raw series for the US are attached in the Appendix as a reference (Figures 12-14).

Correlations between series over time and between countries are also attached in the Appendix, respectively in Table 17 and Tables 18-20.

DCMC - Corporate Debt Capital Markets Starting from the Thomson One Bond database, data are first filtered by issuer geography and then grouped by issuance day. Governments and governmental agencies are excluded. Values are calculated as the monthly sum of proceeds amount (including over-sold) in the domestic market. Volumes are calculated as the monthly count of different issuances. Multiple tranches of the same issuance, defined as an issuance by the same issuer that happened on the same day (e.g. a 5-year bond plus a 7-year bond), are counted as one in the volumes, while values are summed. Deals without at least one recorded book-runner are excluded, consistently with industry common practice when producing aggregate measures. This specification is the complement to DCMG, as together they account for the entire Thomson One Bond database. It instead includes DCMCC.

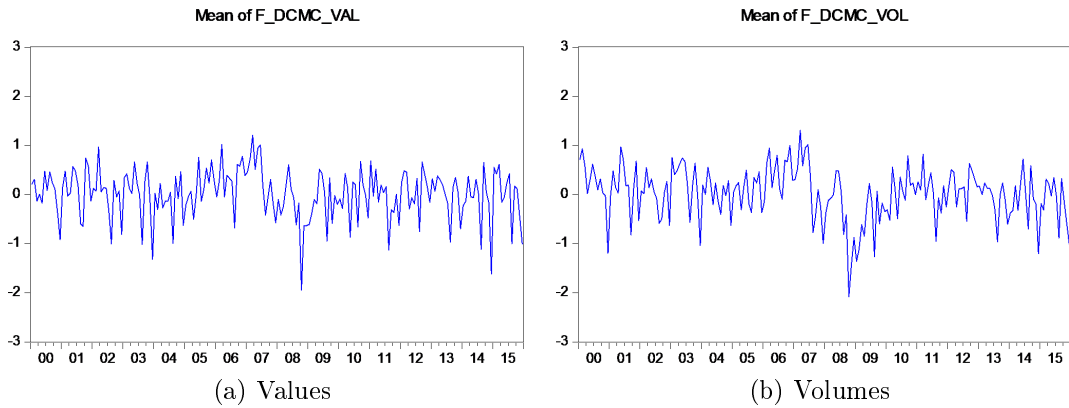


Figure 4: Post-Transformation DCMC Over Time: Cross-Sectional Mean

When conducting a graphical analysis of the noisy series, it is possible to identify:

- (i) a run-up in deals during the years that led to Lehman, in line with the leveraging

occurred globally; (ii) a significant drop in the last quarter of 2008; (iii) a recovery from mid-2009 onwards, but with a lower average.

DCMCC - Core Corporate Debt Capital Markets Variables are obtained exactly as in the DCMC case, but excluding Issue Type Mortgage-backed and Asset-backed. As noted above, this measure is included in DCMC.

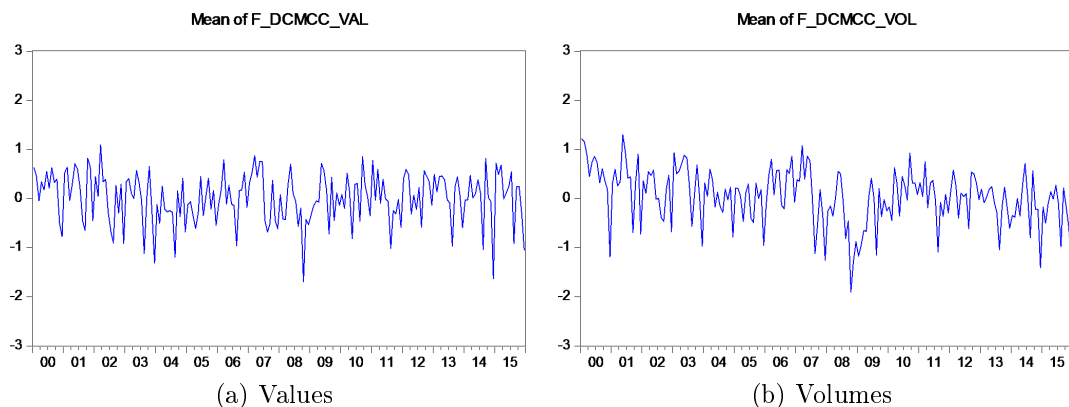


Figure 5: Post-Transformation DCMCC Over Time: Cross-Sectional Mean

Differently from DCMC, here the post-crisis average value is not clearly below pre-crisis levels. Other identified patterns hold.

DCMG - Government Debt Capital Markets Methodology is the same as DCMC, but the sample is filtered by issuer for Governments and Governmental Agencies only. This specification is the complement to DCMC, as together they account for the entire Thomson One Bond database.

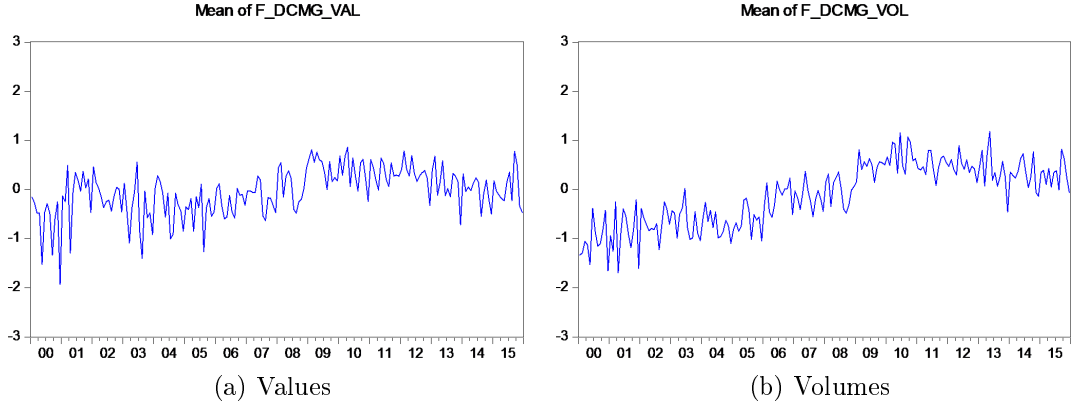


Figure 6: Post-Transformation DCMG Over Time: Cross-Sectional Mean

From Figure 6, we can see a neat upward trend, peaking during the crisis and staying flat at a higher level afterwards. This is in line with expectations, as a consequence of fiscal reactions to the Great Recession across the sample.

ECM - Equity Capital Markets Starting from the Thomson Reuters Equity database, the filtering methodology followed is exactly the same as in DCM, including treatment of multiple tranches of same issuance. This specification includes IPO.

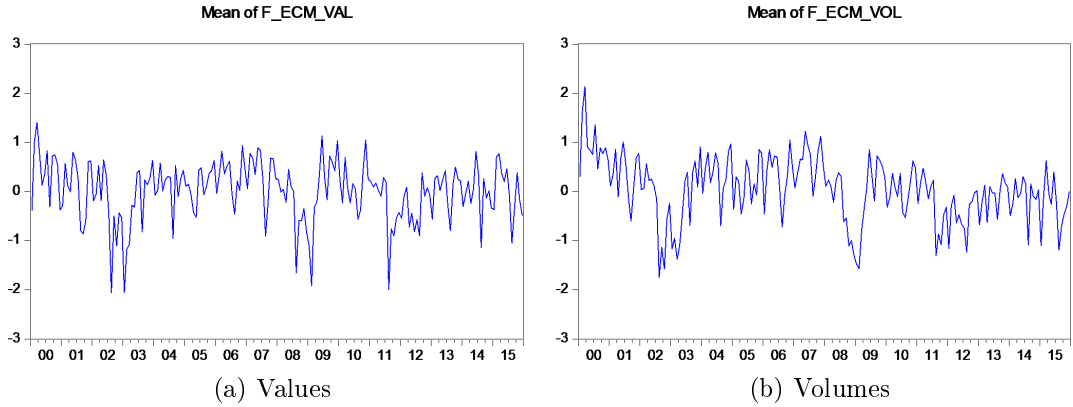


Figure 7: Post-Transformation ECM Over Time: Cross-Sectional Mean

ECM displays three cycle lows in 2002, 2008/2009 and 2011. Interestingly, when looking at values, the rebound in 2009 is higher than the 2006 peak.

IPO - Only IPOs Starting from ECM, we remove every issue type different from “IPO”. In this way we remove the impact of secondary offerings and right issues.

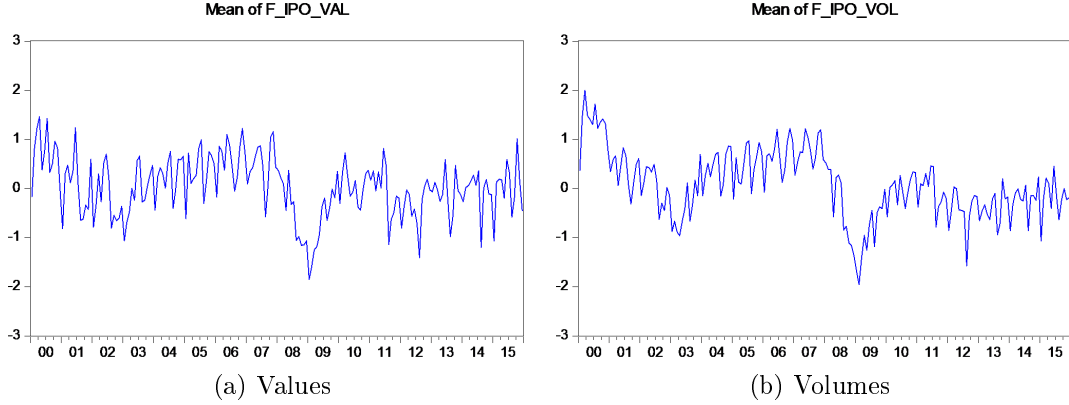


Figure 8: Post-Transformation IPO Over Time: Cross-Sectional Mean

Differently from ECM, IPO displays a very profound drop in 2008-2009, and stays at a lower level even after the recovery. We do not see the over-rebound here.

MA - M&A Completed or Pending We start from the Thomson One Merger database and we filter by geography of the target, and group by announcement day. Values are summed over ranking value (including net debt of target). We select only deals registered as completed, partially completed, pending and pending regulatory approval. We exclude rumored, intended, seeking buyer, unknown and withdrawn deals. This filtering is standard practice in the industry, and required to analyze deal-flow as recent as December 2015. Including only completed deals would produce an artificial decrease in activity in the most recent months. When a deal is recorded more than once due to multiple buyers acquiring the same asset, the deal is counted as one in volumes, while the transacted values are summed over.

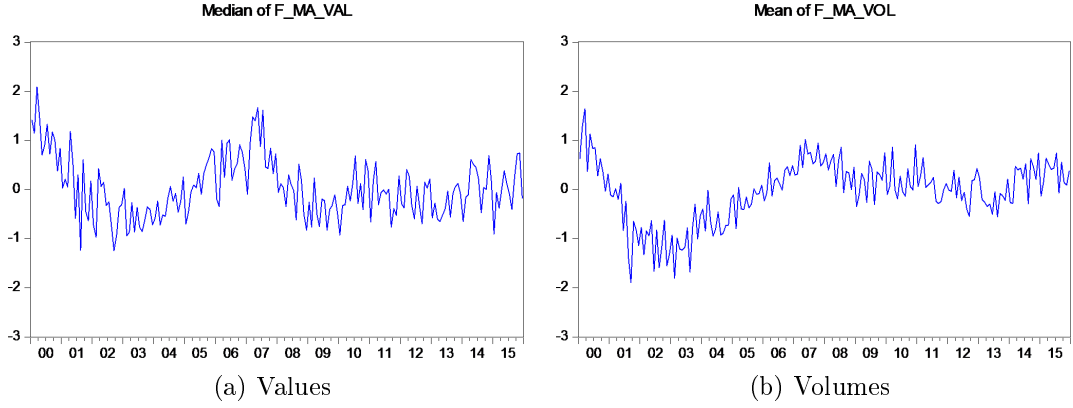


Figure 9: Post-Transformation MA Over Time: Cross-Sectional Mean

M&A cycles are well recognizable. As widely known, M&A activity peaked in 2007, and in real terms has not yet reached those values again. In terms of volumes, instead, the peak was less pronounced: this can be interpreted as a signal of progressively bigger deals on average, during the months that led to the financial crisis.

MAW - M&A Withdrawn We proceed exactly in the same way as in MA, but we include only deals categorized with the status “withdrawn”.

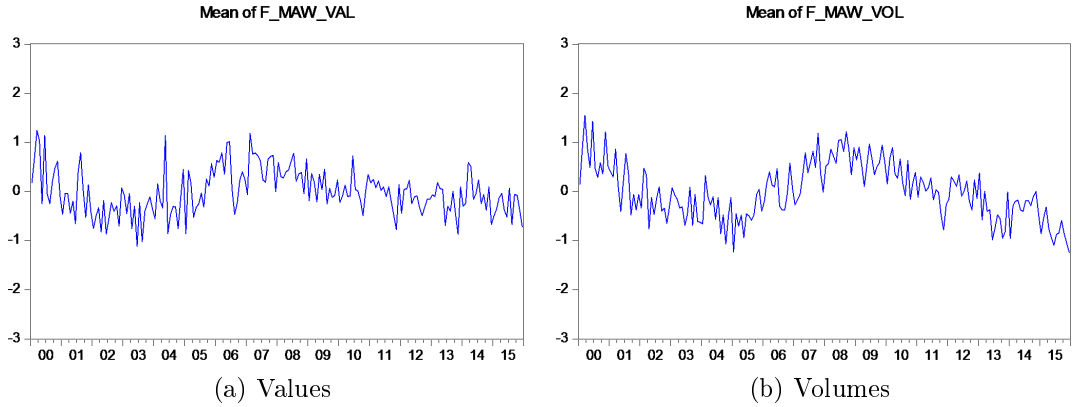


Figure 10: Post-Transformation MAW Over Time: Cross-Sectional Mean

M&A withdrawn is more difficult to interpret as the series itself cannot be considered fully representative of the interrupted deals. Indeed, it captures only the deals announced

and then withdrawn, which can bring some biases in the interpretation. Nevertheless, we can see some interesting patterns when compared with the MA series: the number of M&A deals withdrawn is positively correlated with the number of deals announced in the previous periods and negatively correlated with the economic cycle.

4.2.3 Controls

Our panel study has a very general scope. Indeed, our aim is to investigate the effect of uncertainty on 7 different transaction specifications, in 8 different countries. Therefore, beyond the problem of over-fitting, we face two additional constraints: symmetry and data availability. In fact, in order to derive meaningful conclusions on the different impact of uncertainty on the various transaction families and countries, we need to proceed in a symmetric way and use the same independent variables for each regression. In this context, we are limited by data availability in the various countries.

After analyzing literature on corporate transaction waves, and finding some regularities in the results, our choice is then to include as control the industrial production, the domestic equity market index, and the domestic 10-year government reference yield, as well as one lag of the dependent variable. In our opinion, this represents a comprehensive set, able to capture the economic cycle, the investors' risk appetite, the health of the equity markets, the cost of capital, the current monetary policy stance, and the state of the wave.

As per specification of the variables, we finally decide to take the level of industrial production and stock market and the first difference in the interest rate. Indeed, levels of interest rates are not stationary (i.e. downward trending) over the sample and seldom significant.

All the controls are tested in levels, with 1, 3, 6 and 12 lags, and in differences. However, since a step-wise and swap-wise analysis is not conclusive on which definition of the control was the best suited for all 7 dependent variables, we also include in the Appendix a full output with all the controls both in levels and in first differences (Table 23). Our final choice seems to us a good compromise between simplicity and completeness, and should avoid over-fitting and multicollinearity problems.

In the final data-set, we standardize every control country by country, in order to make them comparable (e.g. the stock market indices have different base levels).

Industrial Production: measure of the economic cycle As discussed in literature review, most of corporate finance transactions are impacted by the macroeconomic cycle in a way or the other.

In our data-set we include the logarithm of the domestic industrial production as an indicator of the economic cycle, which is available at monthly frequency. Later, we will substitute the industrial production with the GDP, showing robustness to the cycle control specification.

We retrieve data from the National Institute of Statistics for each country.

Domestic Equity Market Index: measure of the risk appetite and capital availability Looking at literature, another widely adopted indicator of corporate finance activity is the stock market level and returns. Indeed, it can be considered as a proxy of investor sentiment and risk appetite, as well as a measure of capital availability.

In our data-set, we include the logarithm of the domestic reference stock market (outlined in Table 11) level.

We retrieve data from Bloomberg, and express them in real terms by dividing the raw data by the CPI.

Domestic Interest Rate: measure of the cost of capital and monetary policy stance As expected, literature has found significant relationship between interest rates and transaction waves. First of all, it is a measure of the risk free cost of capital. But it also reflects the central bank monetary policy stance - topic that has gained a lot of relevance over the last decade.

In our data-set we include the logarithm of the 10-year reference government bond yield in in first differences, in order to avoid non-stationarity, and also because it is more relevant in explaining the data.

We retrieve data from Bloomberg.

First Lag of the Dependent Variable: measure of the stage of the wave As discussed in depth in the previous pages, corporate finance transactions happen in waves (i.e. they are auto-correlated). Therefore, one lag of the dependent variable is always significant as a control for the state of the wave.

Tested but Excluded Controls Apart from GDP, which is used in the quarterly model (infra), we test and exclude several controls that do not improve results, and are highly correlated with the chosen ones. Some examples are:

Cycle	ISM Manufacturing Index, ISM Non-Manufacturing Index (Business Services) or equivalent;
Market	1-year return, average daily return of the stock market;
Rates	1-year reference government bond yield, Libor rate or equivalent.

4.2.4 Seasonal Adjustment

As known and observed in literature, corporate finance transactions tend to be seasonal. For example, Summer and Christmas time are usually more quiet than March or May, mirroring the seasonality of the financial markets.

We therefore include a dummy-variable seasonal adjustment, by adding 11 dummy regressors, one per month with the constant absorbing December value.

4.2.5 Pre-regression Diagnostics: Unit Root

We test for the presence of unit root for each of the dependent variables. We always reject both the null hypothesis of having a common unit root process and having an individual unit root process. Results for the standard unit root family tests are shown in Table 21 in the Appendix.

4.3 Regression and Results

4.3.1 Methodology

We perform a panel least square regression on 192 periods and 8 cross-sections. We lose 1 period per cross-section due to the presence of lagged and differentiated values. Missing data on some of the countries (see Table 16) make the panel an unbalanced panel and further reduce the number of data points to 1,279.

As common when dealing with a multi-country panel, we include cross-section fixed effects. This should capture the different state of the market in the different countries, beyond what already neutralized by the standardization.

Furthermore, due to the presence of auto-correlation (between-period correlation) and heteroscedasticity in the error terms of some of the individual series, we use period robust standard errors as per White (1980). Indeed, the White period robust coefficient variance estimator is designed to accommodate arbitrary serial correlation and time-varying variances in the disturbances.

4.3.2 Results Significance

Table 6 synthetically displays the results for the 14 regressions over the 17 regressors (1 study variable, 3 exogenous controls, 1 lag of the dependent variable, 12 constants for seasonal adjustment).

Dep. Var.	F_DCMC_VA... F_DCMC_VO...	F_DCMC_V... F_DCMC_VO...	F_DCMG_VA... F_DCMG_VO...	F_ECM_VAL	F_ECM_VOL	F_IPO_VAL	F_IPO_VOL	F_MA_VAL	F_MA_VOL	F_MAW_VAL	F_MAW_VOL			
UIX	-0.154618 (0.0673)**	-0.178665 (0.0697)**	-0.125218 (0.0702)*	-0.168036 (0.0746)**	0.022219 (0.0342)	0.000621 (0.0432)	-0.133676 (0.0545)**	-0.107544 (0.0526)**	-0.208034 (0.0349)**	-0.124932 (0.0309)**	-0.008600 (0.0243)	0.047607 (0.0260)*	0.110870 (0.0385)**	0.146217 (0.0331)**
LMKT	0.091580 (0.0329)**	0.016793 (0.0326)	0.103877 (0.0374)**	0.006584 (0.0376)	0.054200 (0.0878)	0.022678 (0.0762)	0.218960 (0.0543)**	0.169072 (0.0537)**	0.185429 (0.0682)**	0.208271 (0.0542)**	0.309891 (0.0409)**	0.130689 (0.0671)*	0.176892 (0.0406)**	0.143627 (0.0583)**
LIP	0.024336 (0.0542)	0.047490 (0.0687)	-0.004459 (0.0625)	0.061765 (0.0852)	-0.168384 (0.0709)**	-0.081807 (0.0584)	-0.091298 (0.0199)**	-0.036456 (0.0412)	-0.040226 (0.0435)	0.001998 (0.0425)	0.110645 (0.0250)**	0.062825 (0.0396)	0.105762 (0.0293)**	-0.016330 (0.0711)
D(LR)	-0.348768 (0.1730)**	-0.363377 (0.1048)**	-0.349497 (0.1845)*	-0.354908 (0.1207)**	-0.554396 (0.1022)**	-0.491992 (0.0623)**	0.335910 (0.1318)**	0.289552 (0.1062)**	0.191004 (0.0827)**	0.087813 (0.0415)	0.116207 (0.0866)	0.217925 (0.1085)**	-0.079301 (0.1298)	-0.048182 (0.0606)
LAG1	0.293464 (0.1058)**	0.495616 (0.1015)**	0.211353 (0.0937)**	0.417339 (0.1201)**	0.291867 (0.0840)**	0.489249 (0.0785)**	0.207987 (0.0391)**	0.547451 (0.0673)**	0.242930 (0.0416)**	0.465650 (0.0772)**	0.124683 (0.0185)**	0.634093 (0.0609)**	0.133527 (0.0430)**	0.410125 (0.0740)**
C	-0.585476 (0.1213)**	-0.560346 (0.2002)**	-0.647043 (0.1480)**	-0.680063 (0.2077)**	-0.396571 (0.2865)	-0.340112 (0.2714)	0.058766 (0.0432)	0.093029 (0.0498)*	0.064811 (0.0931)	0.099344 (0.1049)	0.109578 (0.0881)	0.322498 (0.0986)**	-0.001918 (0.1051)	-0.054046 (0.0935)
DUM_JAN	0.850435 (0.3198)**	0.740231 (0.4820)	1.004276 (0.3367)**	0.977621 (0.4835)**	0.790211 (0.5676)	0.541031 (0.5905)	-0.355673 (0.0911)**	-0.715360 (0.1602)**	-0.545035 (0.1939)**	-0.652410 (0.2094)**	-0.466854 (0.1891)**	-0.508879 (0.1674)**	-0.184210 (0.0570)**	-0.112274 (0.1204)
DUM_FEB	0.613514 (0.0999)**	0.603985 (0.1565)**	0.689047 (0.1527)**	0.666209 (0.2020)**	0.547164 (0.2947)*	0.451513 (0.3011)	-0.052806 (0.1301)	0.108636 (0.1689)	0.072556 (0.1561)	0.043512 (0.2203)	-0.122445 (0.1576)	-0.437575 (0.2472)*	0.188090 (0.1546)	0.288828 (0.1502)*
DUM_MAR	0.936264 (0.1647)**	0.949451 (0.2564)**	0.966261 (0.2091)**	0.965715 (0.3065)**	0.339692 (0.3731)	0.177573 (0.3543)	0.238231 (0.1197)**	0.225315 (0.1572)	0.060717 (0.1230)	0.042621 (0.1477)	0.018554 (0.0757)	0.126664 (0.1594)	0.219161 (0.1565)	0.224170 (0.1391)
DUM_APR	0.413603 (0.1404)**	0.329323 (0.2266)	0.581936 (0.1756)**	0.562678 (0.2463)**	0.358410 (0.3234)	0.391497 (0.2569)	-0.214583 (0.1582)	-0.383290 (0.1777)**	-0.101317 (0.1952)	-0.188256 (0.1896)	-0.068054 (0.0969)	-0.571441 (0.1663)**	0.043061 (0.1763)	-0.037603 (0.1376)
DUM_MAY	0.753724 (0.1720)**	0.772675 (0.2414)**	0.864836 (0.1739)**	0.982290 (0.2358)**	0.484446 (0.3108)	0.486017 (0.2473)**	0.085327 (0.1344)	0.079664 (0.1144)	-0.020609 (0.1841)	-0.109060 (0.1884)	-0.013739 (0.1170)	-0.314696 (0.1220)**	0.108453 (0.1057)	0.052596 (0.1454)
DUM_JUN	0.781732 (0.1409)**	0.877973 (0.2063)**	0.785112 (0.1826)**	0.952567 (0.2225)**	0.577570 (0.2966)*	0.548006 (0.2590)**	0.271136 (0.1094)**	0.198872 (0.1230)	0.261809 (0.1291)**	0.165040 (0.1175)	-0.121358 (0.2138)	-0.330391 (0.1535)**	-0.019501 (0.1495)	0.114679 (0.0945)
DUM_JUL	0.566948 (0.1698)**	0.339406 (0.2142)	0.580097 (0.2179)**	0.489814 (0.2516)*	0.267094 (0.3289)	0.226945 (0.3370)	-0.072412 (0.1250)	-0.168284 (0.1399)	0.046559 (0.1142)	-0.015753 (0.1515)	0.009483 (0.1499)	-0.164381 (0.1328)	0.075656 (0.1410)	0.068842 (0.1381)
DUM_AUG	-0.209298 (0.1500)	-0.079096 (0.1668)	-0.092856 (0.1521)	0.023488 (0.1845)	0.015041 (0.2035)	0.053945 (0.1689)	-0.983873 (0.1959)**	-0.862645 (0.1833)**	-0.805621 (0.1732)**	-0.739646 (0.1942)**	-0.373437 (0.1997)*	-0.787662 (0.2714)**	-0.214408 (0.1328)	0.036726 (0.0830)
DUM_SEP	1.066047 (0.2114)**	1.019001 (0.2672)**	1.009552 (0.2488)**	1.085159 (0.2847)**	0.615382 (0.3208)*	0.418807 (0.3326)	0.160159 (0.0718)**	0.224196 (0.0879)**	-0.118739 (0.0843)	0.024414 (0.0840)	-0.146855 (0.0714)**	-0.093006 (0.1054)	-0.032236 (0.1503)	0.014451 (0.1408)
DUM_OCT	0.543434 (0.1466)**	0.443287 (0.2015)**	0.627266 (0.1956)**	0.620378 (0.2346)**	0.400752 (0.3426)	0.484739 (0.2873)*	0.063654 (0.0701)	-0.018580 (0.1105)	0.277878 (0.1166)**	0.154780 (0.1603)	0.026917 (0.1482)	-0.227787 (0.1065)**	-0.162425 (0.1670)	-0.058237 (0.1378)
DUM_NOV	0.670109 (0.1721)**	0.630359 (0.2437)**	0.719807 (0.1785)**	0.735850 (0.2349)**	0.324562 (0.2559)	0.317367 (0.2774)	0.210898 (0.1020)**	0.192015 (0.0915)**	0.096884 (0.1054)	0.040882 (0.1159)	-0.072118 (0.1284)	-0.484186 (0.1472)**	-0.044683 (0.1591)	0.042195 (0.0933)
Observations...	1279	1279	1279	1279	1279	1279	1279	1279	1279	1279	1279	1279	1279	1279
R-squared:	0.2695	0.4235	0.2064	0.3464	0.1814	0.2668	0.2571	0.5172	0.2989	0.4654	0.2140	0.5395	0.0942	0.2346
F-statistic:	20.1345	40.0863	14.1875	28.9216	12.0929	19.8603	18.8830	58.4610	23.2619	47.5108	14.8565	63.9333	5.6750	16.7229

Table 6: Regression Results for the 14 Series in the Main Panel Specification
*Standard Error in Brackets: ** indicates significance at 1%; * indicates significance at 5%; * indicates significance at 10%*

As shown by the standard errors in brackets, uncertainty has a statistically significant negative effect on values and volumes of DCMC, DCMCC, ECM, IPO. Instead, MAW values and volumes seem positively impacted. On DCMG and MA the effect is either small or insignificant.

As expected, both the lag of the dependent variable and the seasonal dummies are widely significant, reflecting the auto-correlated and seasonal nature of the series.

The stock market is significant and positive in all equity and M&A regressions, as well as in DCMC and DCMCC when considering values.

The economic cycle is significant and positive in MA and MAW values, negative in ECM values and DCMG values.

The change in interest rates is negatively strong and significant in all DCM variables, positive in ECM, IPO values and MA volumes.

Illustratively, results for the US only are available in the Appendix in Table 22. In this sub-sample, results mainly hold, excluding MAW and ECM in values. Results generally hold also in other single-country sub-samples.

4.3.3 Explanatory Power: Semi Partial R-Squared

In order to investigate the explanatory power of the UX regressor, we perform a semi-partial R-squared analysis, as shown in Table 7, where are also available the overall R-squared and the R-squared without the AR(1) term as a reference.

Regression	UIX semi-partial R-squared	Overall R-squared	R-squared w/out AR(1) term
DCMC_VAL	0.0192	0.2695	0.2008
DCMC_VOL	0.0237	0.4235	0.2292
DCMCC_VAL	0.0129	0.2064	0.1690
DCMCC_VOL	0.0213	0.3464	0.2044
DCMG_VAL	0.0006	0.1814	0.1051
DCMG_VOL	0.0001	0.2668	0.0570
ECM_VAL	0.0134	0.2571	0.2232
ECM_VOL	0.0088	0.5172	0.3020
IPO_VAL	0.0321	0.2989	0.2540
IPO_VOL	0.0118	0.4654	0.3125
MA_VAL	0.0001	0.2140	0.2013
MA_VOL	0.0018	0.5395	0.2322
MAW_VAL	0.0094	0.0942	0.0777
MAW_VOL	0.0153	0.2346	0.0844

Table 7: Explanatory Power Analysis

Adding the UIX regressor improves the goodness of fit by more than 3% only in IPO_VAL regression; more than 2% also in DCMC_VOL, DCMCC_VOL; more than 1% also in DCMC_VAL, DCMCC_VAL, ECM_VAL, IPO_VOL and MAW_VOL.

Since the R-squared without the AR(1) term is in the 5-35% range, we can conclude that the UIX regressor carries a fair degree of explanatory power in the above mentioned regressions.

4.3.4 Economic Relevance

The economic interpretation of the coefficients of the standardized panel regression is summarized in Figure 11.

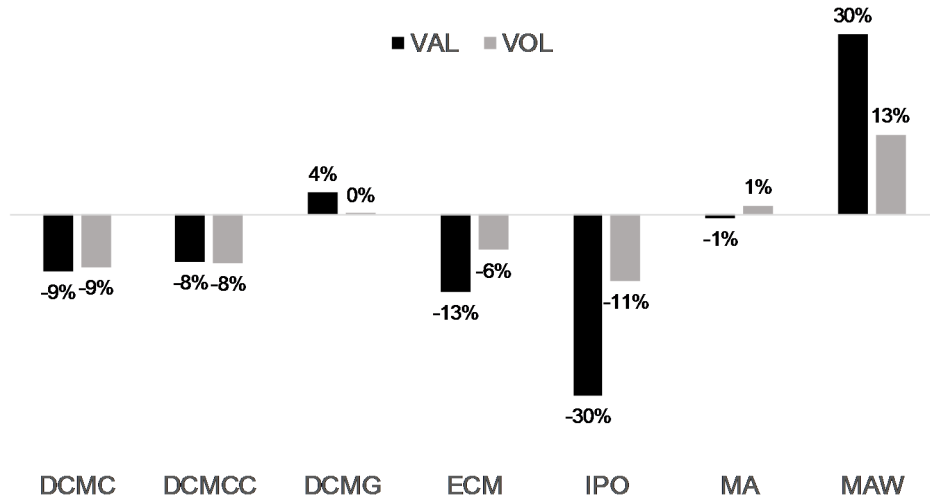


Figure 11: Panel Economic Significance of 1-sigma Increase in the Level of UX - *ceteris paribus* - on the Geometric Mean Level of the Dependent Variables in their Original Form

1-sigma increase in the level of uncertainty translates via the estimated coefficient - *ceteris paribus* - in a similarly subdued activity on the DCMC and DCMCC markets - 8-9% below their geometric mean²⁹, both in values and in volumes. A negative effect is visible also in the Equity Markets, with IPO values down as much as 30%, and volumes down 11%. For what concerns the broader ECM, values are down 13%, volumes 6% on average (i.e. geometric mean). Conversely, M&A withdrawn spike on average by 30% in values and 13% in volumes.

In absolute values³⁰, taking for example the US market, this would translate in approximately 24 fewer DCMC transactions per month for an indicative dollar loss of \$13bn; 15 fewer DCMCC transactions (\$6bn); 4 fewer ECM transactions (\$1bn); 2 IPOs less (\$600m); and 1 more M&A transaction withdrawn (\$1bn).

To obtain these figures³¹, we reverted both the standardization and the log-transformation

²⁹We use geometric mean because average is calculated on variables in log-terms.

³⁰Monetary values are calculated in real terms, taking as reference CPI the average CPI over the sample.

³¹US data are obtained by applying the US-specific standard deviation in the reverse standardization. Instead, data presented in the rest of the section refer to the full panel, account for the different standard deviations in the reverse transformation and are subsequently aggregated weighting by number of observations.

of the dependent variables. All references are with regards to the geometric mean of the original values, given that the standardization was applied on log-transformed values.

4.4 Robustness and Diagnostics

In the following pages, we check the robustness of our results by analyzing residuals, expanding the controls specifications and discussing usual problems in similar panel least square applications.

4.4.1 Residuals Analysis

Linearity Analysis By looking at residuals plotted against the independent variables, we confirm that, after the transformations, the linear model is suited for the analysis of these data. Charts are available in the Appendix (Figures 15-21).

Homoscedasticity Analysis By looking at residuals plotted against the fitted values coming out of the regression, we do not see major heteroscedasticity problems in all regressions but the MAW ones. However, we used robust standard errors that would limit any problem in this area. Charts are available in the Appendix on Figure 22.

Normality Analysis On Figure 23 QQ plots, we see that the major non-normality problems arise in DCMC, DCMG and MAW values. However, since the sample size is large and we are not making out-of-sample predictions, this should not cause problems to our interpretation of results.

Auto-correlation Analysis As shown in Figure 24-30, residuals display some auto-correlation. This is the main reason behind our choice to use robust standard errors in the regressions.

4.4.2 Omitted Variable Bias

As explained above, we choose to use a comprehensive yet simple set of controls subject to panel data availability. Our analysis includes many of the major variables identified as

relevant by previous literature.

Our results are robust to different specifications of the controls as shown in Table 23.

Results hold for DCMC, DCMCC, IPO and MAW. The only difference is with regards to ECM.

When moving to the quarterly model (infra), we will also show robustness to inclusion of GDP, Investments, and Loans.

4.4.3 Reverse Causation

Given the nature of the series, we are confident enough in ruling out a reverse causation problem, as uncertainty should be a function of many different forces happening at a macroeconomic and geo-political level and should bear little impact from activity on the corporate finance markets.

4.4.4 Inconsistency in the Dynamic Panel

In the specification, our fixed-effects panel regression model uses one lag of the dependent variable: this makes the panel dynamic. As shown by Nickell (1981), since the lag of the dependent variable is necessarily correlated with the error (i.e. there is an endogenous regressor), static panel data estimators such as the fixed effects might be inconsistent. The problem becomes relevant if the cross-sections grow to infinity, but the number of periods is kept fixed. However, since our panel has only 8 cross-sections as compared with 192 periods for the series without missing data, it is unlikely that our OLS estimates are inconsistent.

4.5 Quarterly Model

Moving from the monthly to the quarterly model, we are able to perform some additional analyses.

First of all, we test robustness of the main specification to a different frequency and to the substitution of industrial production control with GDP. Then we test additional

hypotheses related to the behavior of the economy, checking if the impact of uncertainty on corporates recourse of financing on the capital markets is cleaned when including as regressors the level of investments or the level of loans in the economy.

4.5.1 Robustness of the main specification

We substitute industrial production with GDP³². Despite being highly correlated with industrial production, GDP is a more complete proxy of the state of the cycle as it includes also output from the service economy. Looking at data with a quarterly frequency has also the benefit of averaging out some of the noise.

We update each of the series to quarterly frequency, using the exact same procedure respectively employed when collecting monthly data.

Previous results generally hold, and are attached in the Appendix in Table 24.

4.5.2 Investments in the Economy

We collect the series of investments of the GDP computed with the expenditure approach from the National Institutes of Statistics for each country. We then transform them using the usual procedure (i.e. log-transformed and standardized country by country).

In Table 25, we show regression results that hold even when including the investments series.

4.5.3 Loans in the Economy

We collect the series of loans among non financial corporations in the economy from the Bank for International Settlements database. We apply the same transformation as the other nominal variables in the data-set (i.e. divided by CPI, log-transformed, standardized country by country in the panel).

We show in Table 26 that regression results hold also when including the differenced loans series.

³²Subject to exactly the same transformations as the other regressors: log-transformed and standardized country by country.

5 Conclusions

In this section we (i) highlight our interpretation of the results outlined above; (ii) discuss limits of the presented research and suggestions for future research; (iii) summarize and conclude the paper.

5.1 Interpretation

After combining our primary and robustness analysis, we can conclude that uncertainty is a relevant factor that co-causes a good degree of fluctuations in corporate debt capital markets transactions and IPOs. In the other analyzed series this is not necessarily true or confirmed by stretches in the model specifications.

We find that 1-sigma increase in uncertainty reduces on average corporate bond issuance by 8-9% both in values and number of deals. For IPOs the picture is even worse, with number of offerings down 11% and value of offer down as much as 30%.

Our interpretation is that uncertainty is relevant only in the corporate finance transactions where there is the possibility to time the market without too much risk or cost, and where the macro-uncertainty is the main factor affecting the choices of the decision makers. This, for example, means that an M&A transaction may be more exposed to uncertainty at a micro-level inside the negotiations, and once an agreement is reached, relevance of the macroeconomic uncertainty is limited because it is costly and unfeasible to postpone or pull the deal (e.g. adviser fees, break-up clauses, expiry of exclusivity periods).

Furthermore, uncertainty is not significant in the series where some opportunistic or contrarian factors come in to play during highly uncertain times. Some examples of this include: a financing of a Keynesian reaction to a downturn in DCMG; a sell-down via ABO³³ or recapitalization via rights issue in ECM; cross-border acquisition at depressed prices of targets under uncertain environment, fire sale of a division to reduce leverage, strategic acquisition to diversify risk exposure in M&A.

When looking at our results from section 4.5, we see that the recess of debt and

³³ Accelerated book-built offer.

equity capital supply on the public markets is not explained by a fall in investments or loans. We therefore conclude that the reduction in financing on the market is driven by the supply of capital (i.e. the investors) rather than by the demand (i.e. corporates). Therefore, it is the pricing and placement of financial instruments to the public market that present the biggest challenges, as the usual conditions of asymmetric information faced by investors are exacerbated by uncertainty at a macro level.

Our results align with literature on the effect of uncertainty on investments, and they are in accordance with Cao, Duan and Uysal (2013) model, which shows that corporates wait longer to issue debt during high uncertainty times. Our results also fit into the IPO-related literature that briefly considers uncertainty, although in different specifications.

5.2 Limits and Room for Future Research

This paper presents a broad and symmetric analysis. As such, it suffers from a big limitation in the level of detail that each series would deserve. This is true at a narrative level, but it is even more true when considering the choice of controls and the regression analysis from a statistical standpoint.

Especially if considering only one country and one series (e.g. IPO in the US), it is possible to dig much deeper in detail and have a more sophisticated choice of controls³⁴. Future studies can focus on corporate DCM and IPO to increase robustness of these results.

It will be interesting to include in the data-set the 2016-2017 period for the UK, which here is excluded, since the analysis was carried out before any reliable macroeconomic effect of Brexit could be measured.

Geographically, the analysis can be extended to some other countries, as well as it can be focused on a subset of the included ones. Differences between the countries can be investigated to see if different market structures are able to explain different tolerance to uncertainty.

Furthermore, it would be interesting to study in-depth the impact of uncertainty on information asymmetry problems on the IPO and corporate debt market, with a more

³⁴See for example Lowry (2003).

micro-focused approach.

Finally, shifting the focus on the study variable itself - the uncertainty index -, it would be a natural step to scientifically study if a blended index between market and non-market based proxies is able to provide improvements at a general level over the simple use of the VIX. In case of a positive answer, the UIX - or a similarly built index -, can be tested against a numerous set of dependent variables that are thought to be affected by uncertainty, or even used in some trading strategies.

5.3 Summary

In this paper, we investigate the impact of uncertainty on an array of different transaction time series.

Uncertainty is defined as the economic agents inability to evaluate probabilities associated to future events. Differently from risk, pure uncertainty cannot be priced with sufficient confidence, and as such remunerated: therefore, economic agents try and avoid it. The popularity of the concept of uncertainty in the financial press and literature comes as a legacy of the 2008 Great Recession.

Within this study, we start from analyzing the existing works on uncertainty, from both the financial and the academic press, with a special focus on the work of Nicholas Bloom. We structure our review in: (i) the meaning and characteristics of uncertainty; (ii) the impact of uncertainty on different business activities; (iii) the determinants of corporate finance transactions fluctuations over time.

In general, uncertainty has been found to have a short-run negative effect on output – in aggregate or disaggregate form. This impact is conveyed through a variety of channels: real options; risk premium; precautionary savings; growth options.

For what concerns financing activities, Cao et al. (2013) show that, in times of high political uncertainty, borrowing frictions are higher, resulting in a reduced credit supply and increased borrowing costs.

Corporate finance transaction waves have been studied both at a general and at an individual level. Rau and Stouraitis (2011) manage to draw a comprehensive, cross-deal timeline of corporate waves: they start with new issue waves – with seasoned equity

offerings preceding IPO waves; then, merger waves follow; finally, repurchase waves close the cycle. Their work is valuable, when considering that no previous study managed to find a synthesis between the conflicting explanations of the neoclassical and the behavioral schools of thought.

Literature about M&A waves represents an example of these conflicts. Indeed, it is widely acknowledged that merger waves occur in times of sustained economic growth, low interest rates and increasing capital markets activity: this combination of elements typically fits periods of economic recovering and re-engineering of processes following a recession. However, each one of the six merger waves in history has been interpreted in the light of either the neoclassical (sector- and country- focused – Jovanovic and Rousseau, 2002; Harford, 2005; Rodrigues, 2013) or the behavioral theory (and its overvaluation theory of merger waves – Shleifer and Vishny, 2003; Rhodes-Knopf and Viswanathan, 2004), leading to different and often conflicting explanations.

Literature on corporate finance deals has not extensively considered the role of uncertainty, with relevant exception constituted by a couple of IPO studies that explicitly take it into account (Lowry, 2003; Pastor and Veronesi, 2005).

Building on these findings, we hypothesize that uncertainty may have a distinct role in explaining corporate finance fluctuations, even after taking into account the explanatory power brought by macroeconomic and other market variables, and that this role varies, being more powerful for transactions where the pricing of the deal has a greater degree of elasticity to public investor sentiment, and less relevant when pricing is mainly subject to different dynamics.

In order to analyze the impact of uncertainty on corporate finance deals, we first build a quantitative indicator of this phenomenon, drawing on the wide sample of proxies proposed by previous works. Our Uncertainty Index (UIX) combines via principal components analysis market-based and non-market-based variables: the Economic Policy Uncertainty (EPU) Index (Baker, Bloom and Davis, 2012); the implied volatility of the domestic stock market; the implied volatility of the domestic currency; and the realized volatilities of the returns on the domestic equity index, the domestic currency and the 10-year reference government interest rates. The resulting characteristics of UIX are in line

with the features of uncertainty as discussed in literature: (i) cross-country correlations are very high; (ii) it is persistent; (iii) it is right-skewed. Moreover, it is highly correlated with the VIX.

The reference sample for the analysis is a monthly panel spanning across 16 years (Jan-2000 to Dec-2015) and 8 geographical areas: United States, Euro area, United Kingdom, Japan, South Korea, Canada, Russia, India.

We control for risk appetite in the markets, status of the economic cycle, cost of money and monetary policy stance, the auto-correlated nature of the series and seasonality.

Our results show a negative impact of uncertainty on corporate debt issuance and on initial public offerings. Their recess during uncertain times is not explained by fluctuations in investments or loans at the broader economy level.

We observe that these series, that significantly react to uncertainty, are the ones where there is little to no room for uncertainty-driven activity (e.g. fire sale of a division to reduce leverage) and where investor sentiment is thought to be a prominent risk factor, confirming our hypothesis. We also notice that, in these series, delaying or pulling the deal is usually a feasible option. On the other hand, if we look at government debt issuance, M&A activity and total activity on the equity capital markets, we do not identify any significant effect of uncertainty, or we are not able to confirm our findings across different model specifications.

We believe this study suggests further analysis on the role of uncertainty, by focusing for example on specific deal families (e.g. IPOs or corporate DCM) or specific geographies (e.g. the US) to remove data availability constraints and increase the sophistication of the control set to obtain a better interpretation of results (especially regarding the impact of uncertainty on information asymmetry problems). Moreover, it will be undoubtedly interesting to include 2016 and 2017 in the data-set, especially for the UK, as Brexit may represent a rare event in terms of being an uncertainty shock (i.e. not an effect of a macroeconomic or financial shock) both primary and big. Finally, the legitimacy of uncertainty indices, built via a combination of market and non-market proxies, may be worth further investigation.

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7 Appendix

Merger	Factors
Horizontal mergers (1893 - 1904)	Regulation (antitrust law) Technological changes
Increasing concentration (1916 - 1929)	Regulation (antitrust law) Organizational innovation (multi-divisional structure) Technological changes
The conglomerate era (1965 - 1969)	Regulation (antitrust law restricted related acquisitions) Organizational innovation (conglomerated operations) Technological changes (financial engineering)
Hostile takeovers (1981 - 1989)	Deregulation Corporate governance problems (neoclassical hypothesis) Technological changes Market undervaluation of targets
The age of strategic mega mergers (1992 - 2000)	Deregulation Corporate governance problems (neoclassical hypothesis) Technological changes
The rebirth of leverage (2003 - 2007)	Appearance of LBO operations Cheap access to financing (junk bonds)

Table 8: Determinants of US Historical Merger Waves

EPU	Mean	Median	Max	Min.	Std. Dev.	Skew.	Kurt.	Obs.
US	113.9817	102.8323	245.1267	57.2026	37.4608	0.7589	2.9125	192
EU	132.3653	127.6488	304.6032	47.6943	52.8745	0.6086	2.7471	192
UK	145.9021	128.2794	408.4350	29.0270	85.4732	0.8360	3.0562	192
JA	101.2405	95.5844	196.0495	35.1023	35.5907	0.5976	2.7651	192
SK	113.8574	106.3618	274.7870	32.4002	48.2322	0.9952	4.1576	180
CA	129.2294	111.8316	399.8463	39.3227	72.4401	1.1457	4.2464	192
RU	114.9059	99.7333	370.5062	12.3988	68.5618	1.2191	4.6153	192
IN	100.0518	88.1663	283.6891	24.9398	54.6609	1.0943	3.9510	156
All	119.4398	104.6110	408.4350	12.3988	61.0457	1.2824	5.1897	1,488

Table 9: Descriptive Statistics for the EPU

EPU	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.7633	1.0000						
UK	0.7387	0.9143	1.0000					
JA	0.6519	0.5467	0.5499	1.0000				
SK	0.7283	0.6623	0.6007	0.5147	1.0000			
CA	0.7780	0.8549	0.8251	0.5929	0.6186	1.0000		
RU	0.1358	0.4378	0.4092	0.1566	0.0842	0.3997	1.0000	
IN	0.6797	0.6980	0.6994	0.4817	0.5484	0.7305	0.3687	1.0000

Table 10: Cross-country correlation for the EPU

Country	Stock Market Index
US	S&P 500
EU	EUROSTOXX 50
UK	FTSE 100
JA	NIKKEI 225
SK	KOSPI Composite
CA	S&P/TSX Composite
RU	MICEX
IN	NIFTY 50

Table 11: List of Stock Market Reference Indices

Country	Stock Market Volatility Index
US	VIX
EU	VSTOXX
UK	FTSE IVI
JA	VXJ
SK	VKOSPI
CA	VIXC
RU	RTSVX
IN	NVIX

Table 12: List of Stock Market Volatility Indices

Domestic	USD	EUR	GBP	JPY	CHF	AUD	CAD
US	<i>nm</i>	Y	Y	Y	Y	Y	Y
EU	Y	<i>nm</i>	Y	Y	Y	N	N
UK	Y	Y	<i>nm</i>	N	N	N	N
JA	Y	Y	N	<i>nm</i>	N	Y	N
SK	Y	N	N	N	N	N	N
CA	Y	N	N	N	N	N	<i>nm</i>
RU	Y	Y	N	N	N	N	N
IN	Y	N	N	N	N	Y	N

Table 13: Matrix of FX Implied Volatility Selected Pairs

Domestic	USD	EUR	GBP	JPY	CHF	AUD	CAD
US	<i>nm</i>	Y	Y	Y	Y	Y	Y
EU	Y	<i>nm</i>	Y	Y	Y	Y	Y
UK	Y	Y	<i>nm</i>	Y	Y	Y	Y
JA	Y	Y	Y	<i>nm</i>	Y	Y	Y
SK	Y	Y	Y	Y	Y	Y	Y
CA	Y	Y	Y	Y	Y	Y	<i>nm</i>
RU	Y	Y	Y	Y	Y	Y	Y
IN	Y	Y	Y	Y	Y	Y	Y

Table 14: Matrix of FX Realized Volatility Selected Pairs

US	VIX	V_FX	S_MKT	S_FX	S_R	EPU
VIX	1.0000					
V_FX	0.8139	1.0000				
S_MKT	0.9118	0.7414	1.0000			
S_FX	0.6097	0.7443	0.6213	1.0000		
S_R	0.5792	0.5135	0.5346	0.4486	1.0000	
EPU	0.5258	0.4725	0.4323	0.3164	0.2328	1.0000

(a) US

EU	VIX	V_FX	S_MKT	S_FX	S_R	EPU
VIX	1.0000					
V_FX	0.6245	1.0000				
S_MKT	0.9076	0.5620	1.0000			
S_FX	0.5253	0.6528	0.5485	1.0000		
S_R	0.5297	0.4397	0.4658	0.2857	1.0000	
EPU	0.4199	0.2803	0.4218	0.1191	0.3506	1.0000

(b) EU

UK	VIX	V_FX	S_MKT	S_FX	S_R	EPU
VIX	1.0000					
V_FX	0.6600	1.0000				
S_MKT	0.8989	0.5378	1.0000			
S_FX	0.6007	0.6225	0.6053	1.0000		
S_R	0.5070	0.5510	0.4178	0.3781	1.0000	
EPU	0.1492	0.1300	0.1296	-0.0955	0.1385	1.0000

(c) UK

JA	VIX	V_FX	S_MKT	S_FX	S_R	EPU
VIX	1.0000					
V_FX	0.8262	1.0000				
S_MKT	0.8490	0.6721	1.0000			
S_FX	0.5813	0.6779	0.6176	1.0000		
S_R	0.0766	0.0722	0.0861	0.0922	1.0000	
EPU	0.3432	0.4078	0.2576	0.2181	-0.0607	1.0000

(d) JA

SK	VIX	V_FX	S_MKT	S_FX	S_R	EPU
VIX	1.0000					
V_FX	0.7412	1.0000				
S_MKT	0.8845	0.6505	1.0000			
S_FX	0.7217	0.7924	0.6488	1.0000		
S_R	0.4979	0.4730	0.4997	0.4899	1.0000	
EPU	0.4008	0.3883	0.4129	0.3108	0.1124	1.0000

(e) SK

CA	VIX	V_FX	S_MKT	S_FX	S_R	EPU
VIX	1.0000					
V_FX	0.8275	1.0000				
S_MKT	0.9146	0.7664	1.0000			
S_FX	0.5621	0.5975	0.6162	1.0000		
S_R	0.3893	0.4774	0.3910	0.4153	1.0000	
EPU	0.4591	0.2340	0.3511	0.1803	0.1040	1.0000

(f) CA

RU	VIX	V_FX	S_MKT	S_FX	S_R	EPU
VIX	1.0000					
V_FX	0.4318	1.0000				
S_MKT	0.8264	0.1319	1.0000			
S_FX	0.6056	0.6266	0.4323	1.0000		
S_R	0.5128	0.6887	0.3536	0.7242	1.0000	
EPU	0.0369	0.5088	-0.1137	0.2880	0.2563	1.0000

(g) RU

IN	VIX	V_FX	S_MKT	S_FX	S_R	EPU
VIX	1.0000					
V_FX	0.7792	1.0000				
S_MKT	0.8599	0.7250	1.0000			
S_FX	0.5338	0.5999	0.5878	1.0000		
S_R	0.5887	0.5924	0.5340	0.4889	1.0000	
EPU	0.1947	0.2185	0.2654	0.3649	0.2394	1.0000

(h) IN

Table 15: Correlation Tables for the UIX Ingredients

Country	Data Points
US	192
EU	192
UK	192
JA	192
SK	144
CA	157
RU	120
IN	98
Total	1,287

Table 16: Summary of Sample Size by Country

	DCMC		DCMCC		DCMG		ECM		IPO		MA		MAW	
	VAL	VOL	VAL	VOL	VAL	VOL	VAL	VOL	VAL	VOL	VAL	VOL	VAL	VOL
DCMC	VAL	1.0000												
	VOL	0.7712	1.0000											
DCMCC	VAL	0.9352	0.7077	1.0000										
	VOL	0.7265	0.9467	0.7296	1.0000									
DCMG	VAL	0.2110	0.1620	0.2539	0.1716	1.0000								
	VOL	0.1679	0.1669	0.2148	0.1700	0.7044	1.0000							
ECM	VAL	0.2080	0.2018	0.1936	0.2073	0.0442	0.0387	1.0000						
	VOL	0.2228	0.2350	0.1850	0.2317	-0.0440	-0.0671	0.6536	1.0000					
IPO	VAL	0.1787	0.2349	0.1052	0.1932	-0.0675	-0.0815	0.5435	0.5740	1.0000				
	VOL	0.1411	0.1877	0.0557	0.1548	-0.1653	-0.1936	0.4067	0.7143	0.7282	1.0000			
MA	VAL	0.1291	0.1233	0.0917	0.0958	-0.1035	-0.0727	0.1763	0.2766	0.1940	0.2751	1.0000		
	VOL	0.1833	0.1618	0.1497	0.1029	0.0477	0.1562	0.1539	0.3007	0.1529	0.2431	0.4121	1.0000	
MAW	VAL	0.1206	0.1153	0.1028	0.1148	0.0060	0.0413	0.1017	0.1848	0.1264	0.1601	0.2463	1.0000	
	VOL	0.1393	0.1232	0.1358	0.1399	0.1056	0.0741	0.0288	0.1319	0.0125	0.0898	0.0982	0.2855	0.4918
														1.0000

Table 17: Correlation between Dependent Variables for the Full Cross-Section

DCMC_VAL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.4896	1.0000						
UK	0.2933	0.5495	1.0000					
JA	0.2056	0.1900	0.2048	1.0000				
SK	-0.1212	0.3158	0.3704	0.0666	1.0000			
CA	0.5889	0.5026	0.4225	0.3270	0.1901	1.0000		
RU	0.1478	0.1157	0.1113	0.1445	0.1402	0.1859	1.0000	
IN	-0.0274	-0.0172	0.0450	-0.0478	0.0647	0.0523	-0.0957	1.0000

(a) DCMC_VAL

DCMC_VOL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.5129	1.0000						
UK	0.3639	0.5130	1.0000					
JA	0.4202	0.2025	0.1054	1.0000				
SK	0.0473	0.1773	0.4792	-0.0721	1.0000			
CA	0.6295	0.6031	0.3175	0.4653	0.1127	1.0000		
RU	0.4071	0.2453	0.1281	0.4048	-0.0635	0.3428	1.0000	
IN	0.1659	0.0534	0.0863	0.2255	-0.1255	0.1047	0.1645	1.0000

(b) DCMC_VOL

DCMCC_VAL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.4769	1.0000						
UK	0.3336	0.5097	1.0000					
JA	0.1600	0.2640	0.1193	1.0000				
SK	-0.0755	0.3185	0.3202	0.1852	1.0000			
CA	0.5526	0.4664	0.3820	0.2950	0.2234	1.0000		
RU	0.0888	0.0900	0.0317	0.1201	0.1414	0.1721	1.0000	
IN	-0.0197	-0.0198	0.0126	-0.0892	0.0925	0.0526	-0.0951	1.0000

(c) DCMCC_VAL

DCMCC_VOL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.4836	1.0000						
UK	0.3751	0.4505	1.0000					
JA	0.2950	0.2298	0.0572	1.0000				
SK	0.1605	0.1981	0.5458	0.1091	1.0000			
CA	0.5986	0.6022	0.3234	0.4330	0.1628	1.0000		
RU	0.3796	0.2295	0.0412	0.2346	-0.0368	0.3180	1.0000	
IN	0.1804	0.0003	-0.0009	0.0660	-0.1089	0.1365	0.1481	1.0000

(d) DCMCC_VOL

DCMG_VAL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.2719	1.0000						
UK	0.1927	0.4874	1.0000					
JA	0.0947	0.2520	0.0743	1.0000				
SK	-0.1149	0.3655	0.1391	0.0860	1.0000			
CA	0.0709	0.0454	0.1163	-0.1630	-0.1229	1.0000		
RU	-0.0544	-0.0142	-0.0104	0.1071	-0.1209	-0.0390	1.0000	
IN	0.0946	-0.0876	-0.1352	-0.0453	-0.3017	0.1398	-0.0144	1.0000

(e) DCMG_VAL

DCMG_VOL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.0468	1.0000						
UK	0.1036	0.3650	1.0000					
JA	0.0789	0.2356	-0.0224	1.0000				
SK	-0.1118	0.3156	-0.0032	0.3005	1.0000			
CA	0.1041	0.2686	0.1922	0.2890	0.1785	1.0000		
RU	0.2148	-0.0679	-0.2670	0.1338	-0.0994	-0.0479	1.0000	
IN	0.0313	-0.0682	0.0864	-0.0316	-0.2116	0.0100	-0.0409	1.0000

(f) DCMG_VOL

Table 18: Correlation between Dependent Variables Cross-Country (1/3)

ECM_VAL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.5333	1.0000						
UK	0.2057	0.3836	1.0000					
JA	0.2103	0.4297	0.1482	1.0000				
SK	0.1370	0.2269	-0.0002	0.3006	1.0000			
CA	0.0971	0.2283	0.1525	0.2243	0.1672	1.0000		
RU	0.3097	0.1347	0.0074	0.1267	0.0445	0.2188	1.0000	
IN	0.4148	0.1610	-0.0010	0.2172	0.0933	0.0264	0.2237	1.0000

(a) ECM_VAL

ECM_VOL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.6381	1.0000						
UK	0.2205	0.4154	1.0000					
JA	0.3932	0.3319	0.4150	1.0000				
SK	0.0960	0.2770	0.0617	-0.0207	1.0000			
CA	0.3331	0.3395	0.1004	0.0029	0.0912	1.0000		
RU	0.2928	0.2835	0.1293	0.0119	-0.0718	0.5272	1.0000	
IN	0.4273	0.2698	0.0916	0.1829	-0.0822	0.3204	0.4516	1.0000

(b) ECM_VOL

IPO_VAL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.4102	1.0000						
UK	0.3996	0.4460	1.0000					
JA	0.2283	0.2053	0.3495	1.0000				
SK	0.0613	0.2048	0.0910	0.1154	1.0000			
CA	0.3332	0.3065	0.4667	0.1852	0.1775	1.0000		
RU	0.1880	0.1415	0.0753	0.0044	0.2098	0.1907	1.0000	
IN	0.2074	0.1295	0.0237	-0.0816	0.1713	0.1597	0.2449	1.0000

(c) IPO_VAL

IPO_VOL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.3803	1.0000						
UK	0.6012	0.5188	1.0000					
JA	0.1921	0.1016	0.4086	1.0000				
SK	0.1135	0.2529	0.0224	0.0049	1.0000			
CA	0.1789	0.2165	0.0204	-0.0084	0.1876	1.0000		
RU	0.2491	0.2931	0.1946	-0.0549	0.2274	0.3631	1.0000	
IN	0.4214	0.2524	0.2773	0.0769	0.1814	0.3408	0.3499	1.0000

(d) IPO_VOL

MA_VAL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.1138	1.0000						
UK	0.0545	0.4032	1.0000					
JA	-0.1573	0.1134	0.0767	1.0000				
SK	0.1115	0.0839	-0.0077	-0.0636	1.0000			
CA	0.2002	0.1751	0.1503	-0.1049	0.0381	1.0000		
RU	-0.1053	0.0366	-0.0061	-0.2267	0.0578	0.2251	1.0000	
IN	0.0626	0.0177	0.1214	0.1082	-0.1962	-0.0385	-0.0012	1.0000

(e) MA_VAL

MA_VOL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.4395	1.0000						
UK	0.2519	0.4664	1.0000					
JA	-0.0673	0.0567	0.1159	1.0000				
SK	0.1992	0.1968	-0.1780	0.1832	1.0000			
CA	0.0170	0.2415	0.1982	0.2838	0.1418	1.0000		
RU	-0.3947	-0.1300	-0.3526	-0.1902	0.2140	0.1070	1.0000	
IN	-0.0066	0.0589	0.2609	0.2652	-0.0897	0.4235	-0.1059	1.0000

(f) MA_VOL

Table 19: Correlation between Dependent Variables Cross-Country (2/3)

MAW_VAL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	-0.1368	1.0000						
UK	-0.0432	0.2164	1.0000					
JA	0.0426	-0.0404	0.1682	1.0000				
SK	-0.0439	0.0118	0.0073	0.0964	1.0000			
CA	0.1257	-0.1087	-0.0852	0.0691	0.0815	1.0000		
RU	0.0776	-0.0647	0.1416	-0.0878	0.0937	0.0170	1.0000	
IN	-0.2169	0.0259	0.0243	0.1484	-0.1804	-0.0601	-0.0177	1.0000

(a) MAW_VAL

MAW_VOL	US	EU	UK	JA	SK	CA	RU	IN
US	1.0000							
EU	0.2742	1.0000						
UK	0.2058	0.3892	1.0000					
JA	0.5177	0.2229	0.3740	1.0000				
SK	0.3044	0.2379	0.2548	0.4754	1.0000			
CA	0.1342	0.1912	0.1950	0.2031	0.2733	1.0000		
RU	0.1647	0.1909	0.3801	0.2011	0.0658	0.2357	1.0000	
IN	0.1496	0.0162	0.0453	0.1505	0.0893	0.3342	-0.0208	1.0000

(b) MAW_VOL

Table 20: Correlation between Dependent Variables Cross-Country (3/3)

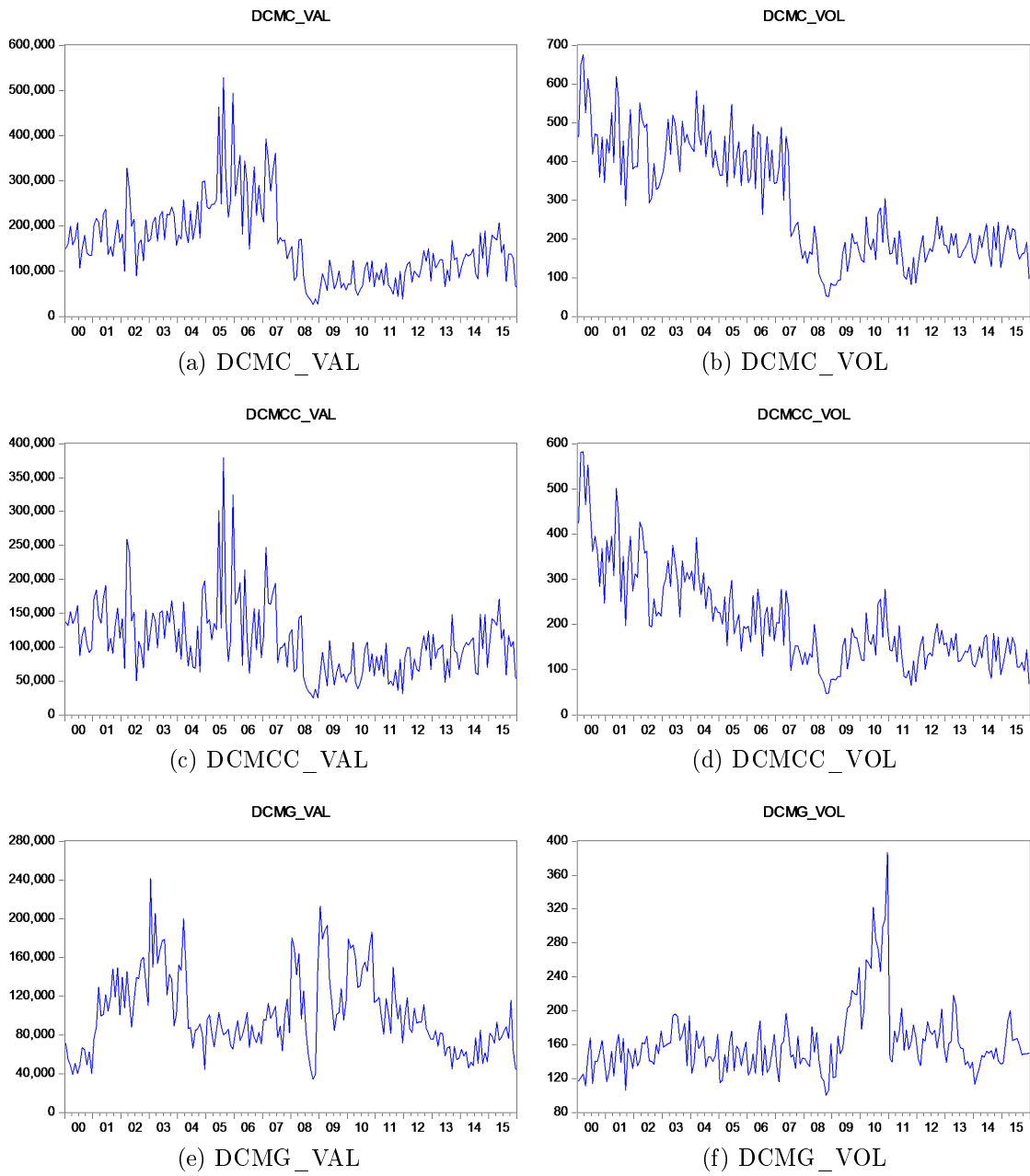


Figure 12: US Raw Variables (1/3)

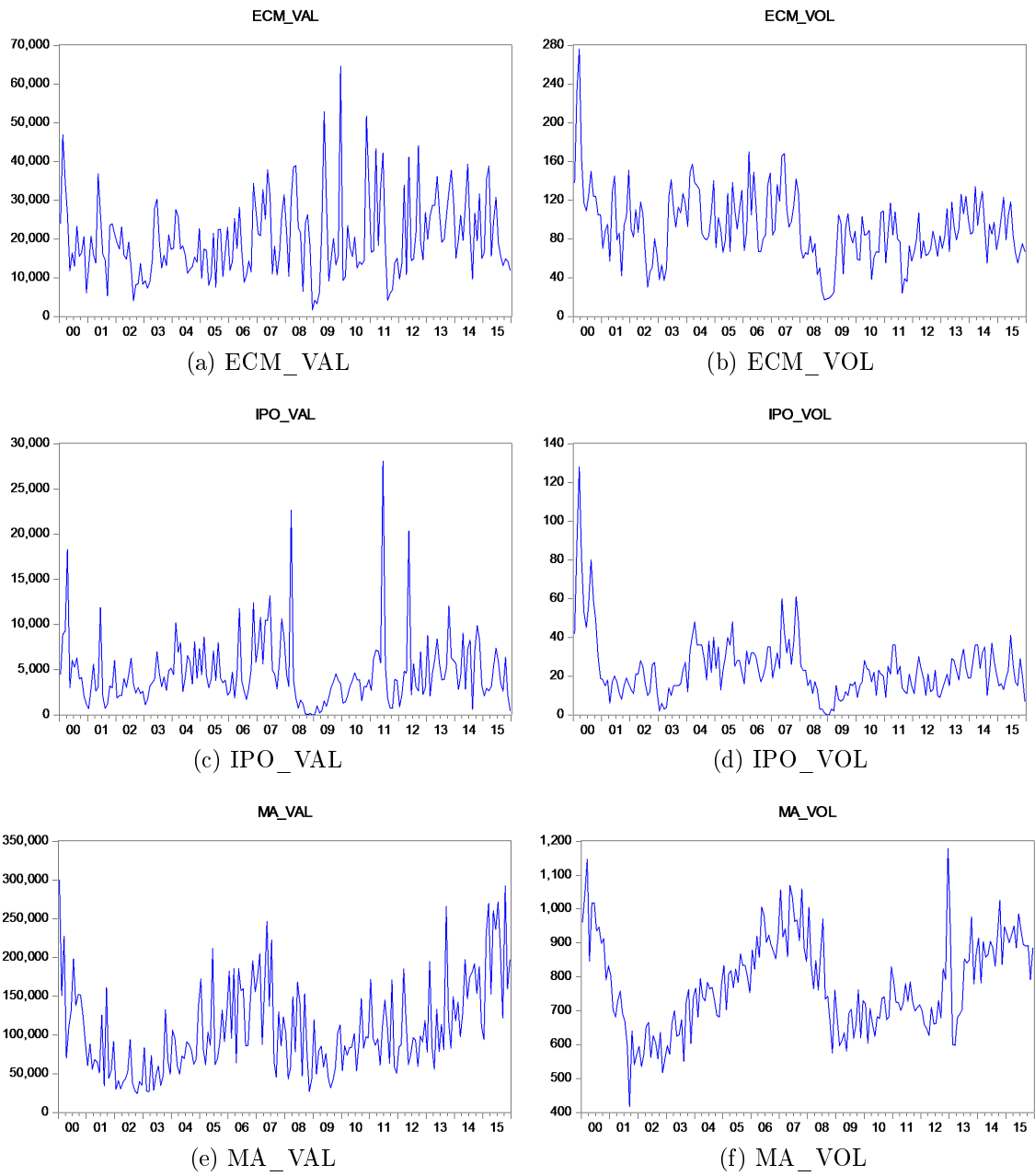


Figure 13: US Raw Variables (2/3)

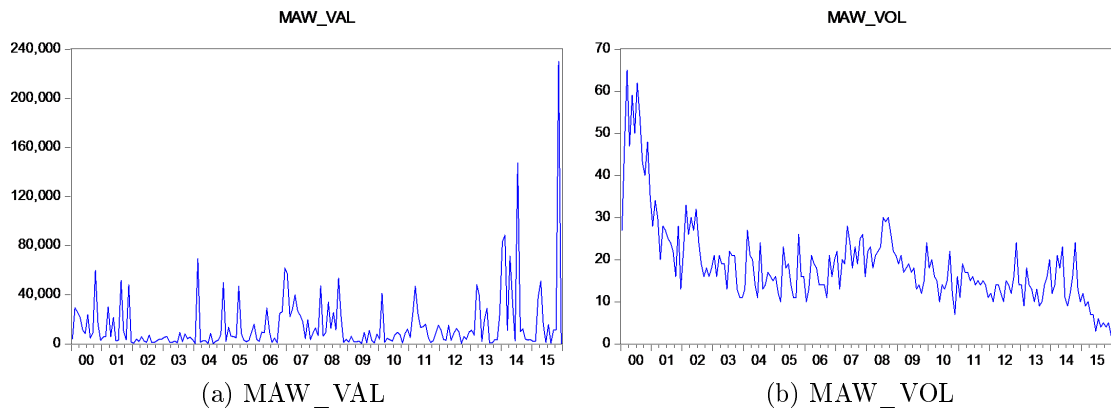


Figure 14: US Raw Variables (3/3)

Method	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
<i>Null: Unit root (assumes common unit root process)</i>	DCMC_VAL		DCMC_VOL		DCMCC_VAL		DCMCC_VOL	
Levin, Lin & Chu t	-21.11	0.0000	-12.62	0.0000	-25.77	0.0000	-15.61	0.0000
<i>Null: Unit root (assumes individual unit root process)</i>								
Im, Pesaran and Shin W-stat	-24.74	0.0000	-17.43	0.0000	-27.96	0.0000	-20.24	0.0000
ADF - Fisher Chi-square	456.13	0.0000	309.87	0.0000	523.39	0.0000	373.00	0.0000
PP - Fisher Chi-square	489.69	0.0000	366.39	0.0000	544.80	0.0000	411.60	0.0000
<i>Null: Unit root (assumes common unit root process)</i>	DCMG_VAL		DCMG_VOL		ECM_VAL		ECM_VOL	
Levin, Lin & Chu t	-23.22	0.0000	-18.17	0.0000	-28.29	0.0000	-15.77	0.0000
<i>Null: Unit root (assumes individual unit root process)</i>								
Im, Pesaran and Shin W-stat	-25.57	0.0000	-20.82	0.0000	-25.72	0.0000	-15.88	0.0000
ADF - Fisher Chi-square	428.11	0.0000	311.76	0.0000	494.48	0.0000	280.16	0.0000
PP - Fisher Chi-square	489.38	0.0000	353.44	0.0000	519.76	0.0000	288.20	0.0000
<i>Null: Unit root (assumes common unit root process)</i>	IPO_VAL		IPO_VOL		MA_VAL		MA_VOL	
Levin, Lin & Chu t	-25.84	0.0000	-14.98	0.0000	-29.68	0.0000	-13.32	0.0000
<i>Null: Unit root (assumes individual unit root process)</i>								
Im, Pesaran and Shin W-stat	-23.90	0.0000	-16.93	0.0000	-26.44	0.0000	-13.17	0.0000
ADF - Fisher Chi-square	448.84	0.0000	283.48	0.0000	496.12	0.0000	208.19	0.0000
PP - Fisher Chi-square	489.51	0.0000	324.39	0.0000	542.82	0.0000	222.17	0.0000
<i>Null: Unit root (assumes common unit root process)</i>	MAW_VAL		MAW_VOL					
Levin, Lin & Chu t	-31.10	0.0000	-20.29	0.0000				
<i>Null: Unit root (assumes individual unit root process)</i>								
Im, Pesaran and Shin W-stat	-29.21	0.0000	-19.94	0.0000				
ADF - Fisher Chi-square	547.40	0.0000	355.31	0.0000				
PP - Fisher Chi-square	574.11	0.0000	399.22	0.0000				

Table 21: Unit Root Test Results

Dep. Var.	F_DCMC_VAL	F_DCMC_VOL	F_DCMCC_VAL..F_DCMCC_VOL..	F_DCMG_VAL	F_DCMG_VOL	F_ECM_VAL	F_ECM_VOL	F_IPO_VAL	F_IPO_VOL	F_MA_VAL	F_MA_VOL	F_MAW_VAL	F_MAW_VOL
UIX	-0.178023 (0.0569)***	-0.151830 (0.0370)***	-0.260846 (0.0739)***	-0.168207 (0.0439)***	-0.042178 (0.0521)**	-0.136816 (0.0621)**	-0.122638 (0.0758)	-0.399774 (0.0815)***	-0.284352 (0.0602)***	0.012423 (0.0754)	-0.050197 (0.0519)	0.048951 (0.0893)	-0.028593 (0.0803)
LMKT	0.004230 (0.0574)	0.013371 (0.0381)	0.133507 (0.0807)*	0.086474 (0.0504)	-0.121241 (0.0669)*	-0.134914 (0.0912)**	0.242985 (0.0673)***	0.061745 (0.0664)	0.123851 (0.0720)*	0.384362 (0.0937)***	0.100555 (0.0644)	0.241859 (0.1043)**	0.052505 (0.0717)
LIP	-0.087100 (0.0530)	-0.136219 (0.0385)***	-0.207275 (0.0749)***	-0.245219 (0.0552)***	-0.106204 (0.0566)*	-0.075663 (0.0636)	-0.129806 (0.0797)	-0.090687 (0.0774)	-0.090249 (0.0598)	0.171659 (0.0798)**	0.172249 (0.0607)***	0.111240 (0.0933)	-0.122907 (0.0676)*
D(LR)	-0.029057 (0.2073)	-0.304667 (0.1335)**	0.052557 (0.2842)	0.285326 (0.1850)*	-0.985664 (0.2206)***	-0.636373 (0.2564)**	1.106981 (0.3166)***	-0.332797 (0.3100)	0.105646 (0.2345)	0.549758 (0.3125)*	-0.140514 (0.2143)	-0.011168 (0.3682)	-0.099016 (0.2489)
LAG1	0.762747 (0.0474)***	0.851851 (0.0329)***	0.483113 (0.0650)***	0.743721 (0.0451)***	0.717540 (0.0569)***	0.685726 (0.0542)***	0.242575 (0.0695)***	0.390420 (0.0698)***	0.626575 (0.0556)***	0.132177 (0.0734)*	0.612206 (0.0614)***	0.100079 (0.0776)	0.785240 (0.0534)***
C	-0.460951 (0.1307)***	-0.389535 (0.0841)***	-0.442182 (0.1792)**	-0.464238 (0.1039)**	-0.369057 (0.1360)***	0.350196 (0.1600)**	-0.071469 (0.2000)	-0.227822 (0.1939)	-0.323176 (0.1497)**	0.044917 (0.1974)	0.469771 (0.1382)***	0.028193 (0.2319)	-0.222623 (0.1580)***
DUM_JAN	0.754810 (0.1886)***	0.387374 (0.1212)***	0.821145 (0.2568)***	0.592558 (0.1503)***	1.157878 (0.1956)***	-1.363754 (0.2304)***	-0.429585 (0.2860)	-0.272656 (0.2786)	-0.395242 (0.2154)*	0.093942 (0.2830)	-0.298475 (0.1983)	-0.295177 (0.3332)	0.158093 (0.2235)
DUM_FEB	0.461982 (0.1852)**	0.430529 (0.1197)***	0.483521 (0.2537)*	0.409073 (0.1475)***	0.372705 (0.1948)*	-0.490106 (0.2319)**	0.012906 (0.2867)	0.345504 (0.2777)	0.741941 (0.2173)***	-0.090988 (0.2814)	-1.038584 (0.1984)***	0.487931 (0.3295)	0.352048 (0.2206)
DUM_MAR	0.746715 (0.1845)***	0.813228 (0.1189)***	0.782982 (0.2530)***	0.952908 (0.1469)***	0.444827 (0.1935)**	0.156242 (0.2286)	0.648855 (0.2824)***	0.374238 (0.2741)**	0.341085 (0.2116)	-0.174020 (0.2768)	-0.267684 (0.1908)	0.071034 (0.3292)	0.424541 (0.2202)*
DUM_APR	0.167914 (0.1650)	-0.012563 (0.1192)	0.197501 (0.2539)	0.001356 (0.1476)**	0.235663 (0.1936)	-0.367163 (0.2261)	-0.054304 (0.2616)	0.401886 (0.2746)	0.419441 (0.2121)**	-0.177992 (0.2768)	-0.543013 (0.1932)***	0.304773 (0.3285)	0.190361 (0.2216)
DUM_MAY	0.721325 (0.1846)***	0.800267 (0.1190)***	0.792434 (0.2532)***	1.032150 (0.1471)***	0.316429 (0.1924)	0.037081 (0.2261)	0.740119 (0.2817)***	0.382809 (0.2750)	0.611806 (0.2117)***	-0.077990 (0.2782)	-0.408192 (0.1921)**	0.030884 (0.3284)	0.238172 (0.2205)
DUM_JUN	0.390261 (0.1848)**	0.390082 (0.1191)***	0.299901 (0.2536)	0.409480 (0.1476)***	0.379434 (0.1923)*	0.013595 (0.2270)	0.433251 (0.2826)	0.511331 (0.2750)*	0.276753 (0.2127)	0.131694 (0.2781)	-0.331369 (0.1935)*	-0.406255 (0.3284)	-0.071621 (0.2210)
DUM_JUL	-0.108794 (0.1848)	-0.252746 (0.1191)**	-0.241841 (0.2534)	-0.281657 (0.1473)*	0.201125 (0.1922)	-0.912159 (0.2283)***	-0.514022 (0.2818)*	0.170506 (0.2759)	0.376132 (0.2121)*	0.295069 (0.2803)	-0.424914 (0.1952)**	0.452596 (0.3299)	0.409137 (0.2202)*
DUM_AUG	0.574597 (0.1872)***	0.482916 (0.1201)***	0.503639 (0.2585)*	0.587587 (0.1493)***	0.335200 (0.1926)*	-0.229267 (0.2270)	-0.354607 (0.2863)	-0.172768 (0.2754)	0.118173 (0.2128)	-0.450557 (0.2826)	-0.595416 (0.1957)***	-0.580547 (0.3302)*	0.013695 (0.2210)
DUM_SEP	0.777201 (0.1850)***	0.596308 (0.1190)***	0.744028 (0.2539)***	0.668325 (0.1472)***	0.203582 (0.1924)	-0.751630 (0.2265)***	0.066925 (0.2883)	-0.046287 (0.2749)	0.081658 (0.2119)	0.021749 (0.2788)	-0.596378 (0.1933)***	-0.291972 (0.3316)	0.190405 (0.2203)
DUM_OCT	0.148290 (0.1849)	0.139205 (0.1191)	0.063335 (0.2534)	0.131978 (0.1471)	0.321084 (0.1921)*	-0.085009 (0.2269)	-0.061947 (0.2839)	0.565260 (0.2751)**	0.853987 (0.2122)***	0.132465 (0.2787)	-0.139462 (0.1920)	-0.211233 (0.3298)	0.359444 (0.2202)
DUM_NOV	0.814631 (0.1850)***	0.689781 (0.1190)***	0.830610 (0.2547)***	0.843821 (0.1476)***	0.233489 (0.1920)	-0.326963 (0.2262)	0.507134 (0.2940)**	0.295067 (0.2745)	0.310309 (0.2122)	-0.250227 (0.2793)	-1.057251 (0.1951)***	0.098073 (0.3290)	0.145822 (0.2201)
Observations:	191	191	191	191	191	191	191	191	191	191	191	191	191
R-squared:	0.7522	0.6967	0.5321	0.8409	0.7323	0.6243	0.4234	0.5076	0.7334	0.4173	0.7337	0.2185	0.6464
F-statistic:	33.0053	94.4256	12.3665	57.4984	29.7442	18.0728	7.9846	11.2094	29.9097	7.7863	29.9891	3.0402	19.8835

Table 22: Regression Results for the US Sub-Sample
Standard Error in Brackets: *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%

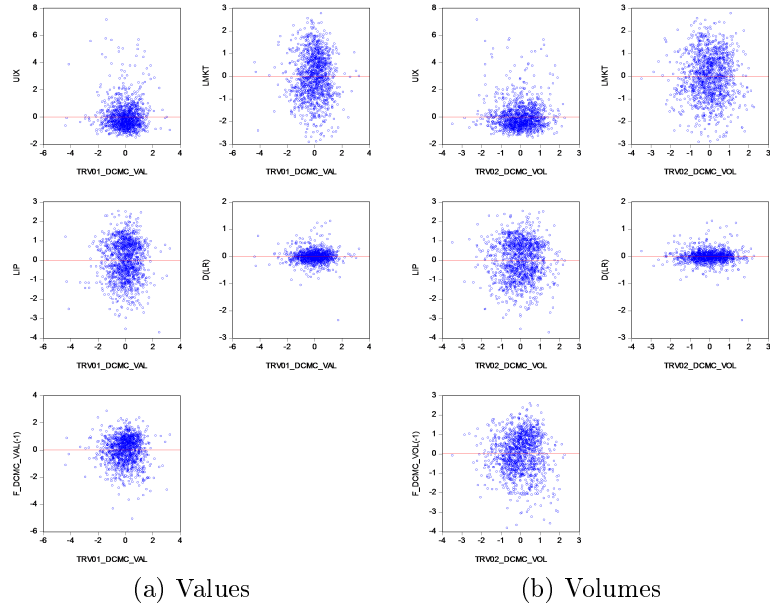


Figure 15: Residuals Diagnostics: Linearity Analysis - DCMC

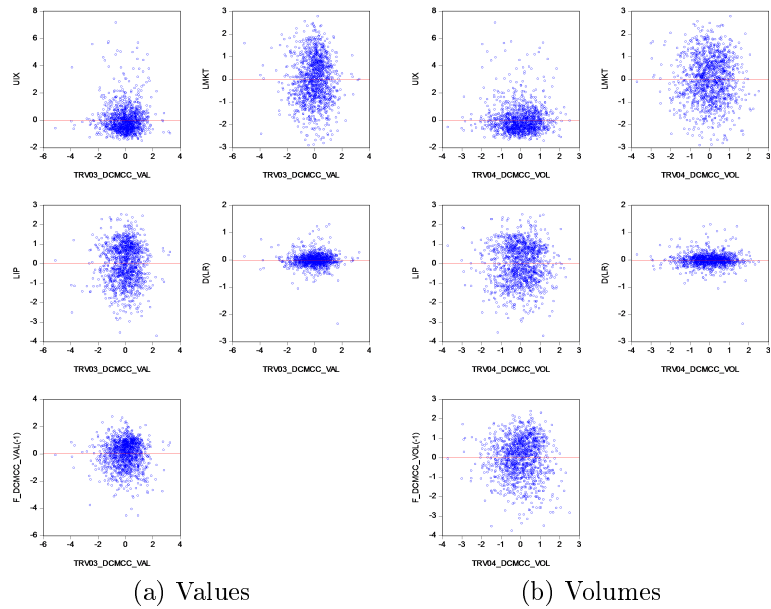
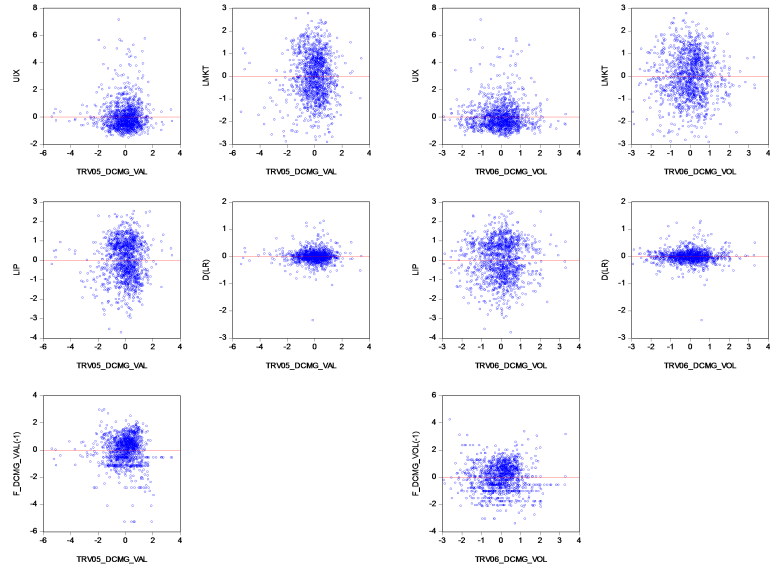


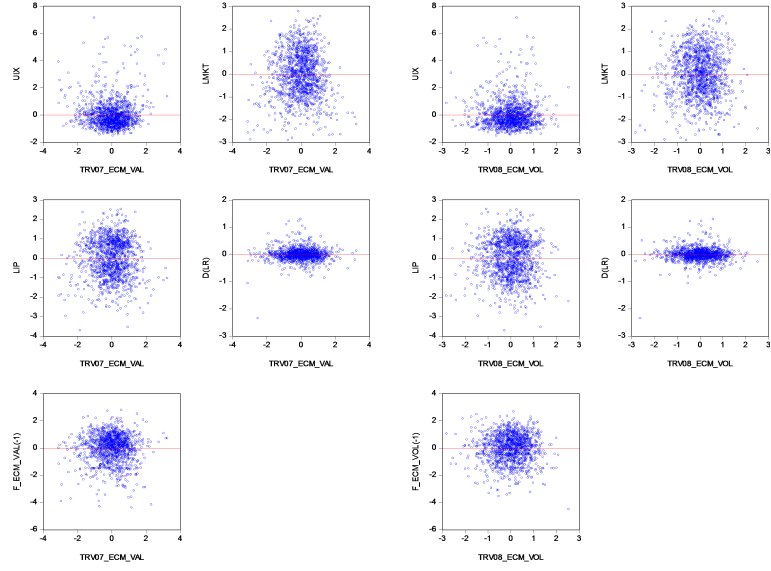
Figure 16: Residuals Diagnostics: Linearity Analysis - DCMCC



(a) Values

(b) Volumes

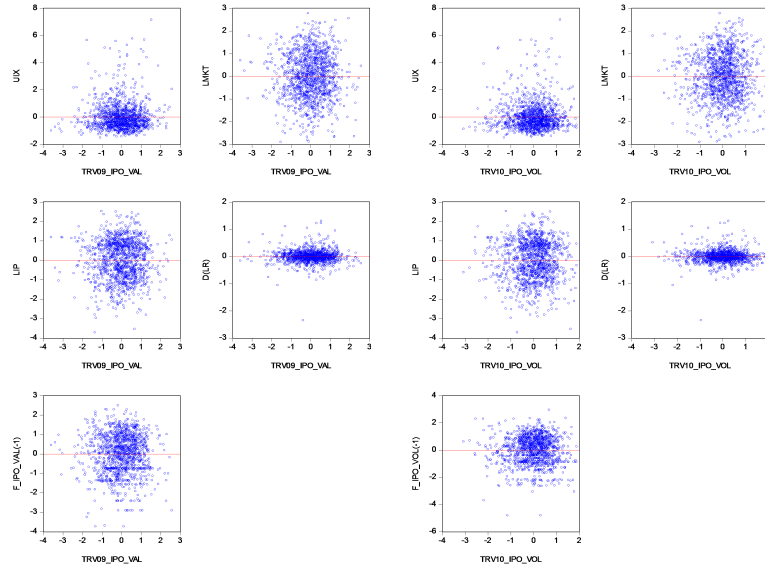
Figure 17: Residuals Diagnostics: Linearity Analysis - DCMG



(a) Values

(b) Volumes

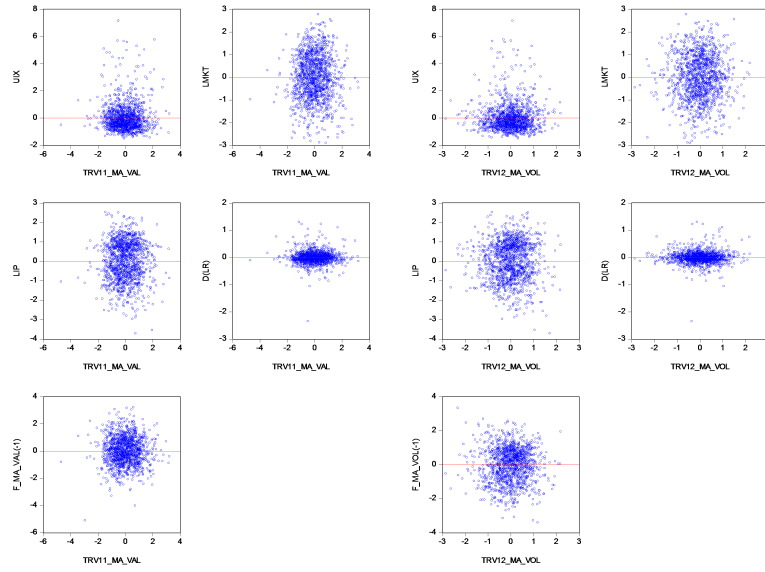
Figure 18: Residuals Diagnostics: Linearity Analysis - ECM



(a) Values

(b) Volumes

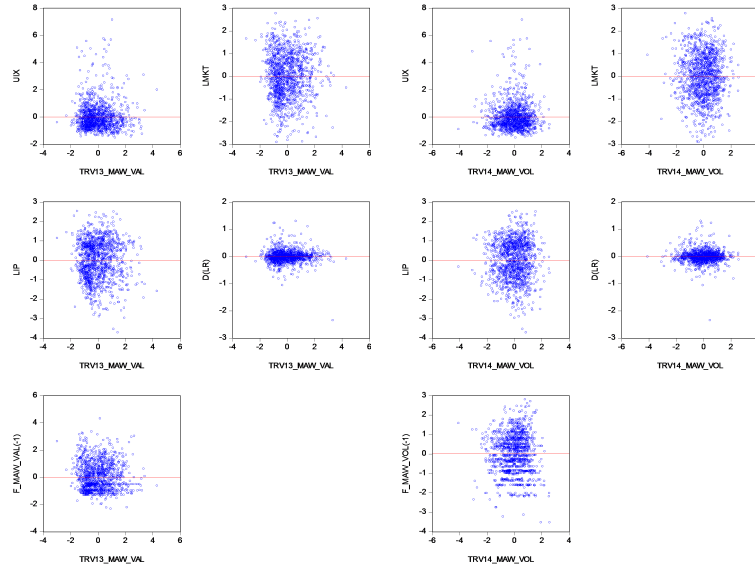
Figure 19: Residuals Diagnostics: Linearity Analysis - IPO



(a) Values

(b) Volumes

Figure 20: Residuals Diagnostics: Linearity Analysis - MA



(a) Values

(b) Volumes

Figure 21: Residuals Diagnostics: Linearity Analysis - MAW

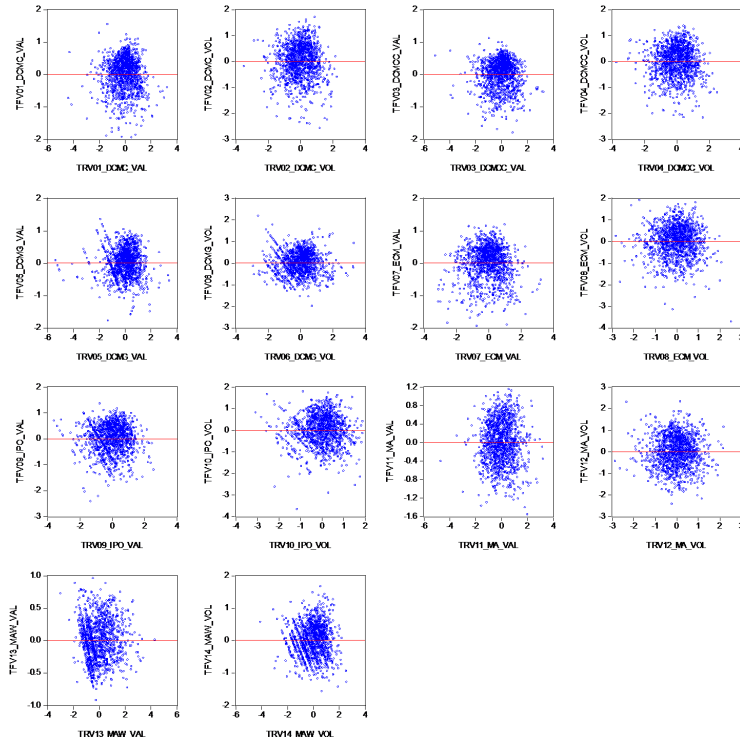


Figure 22: Residuals Diagnostics: Homoscedasticity Analysis

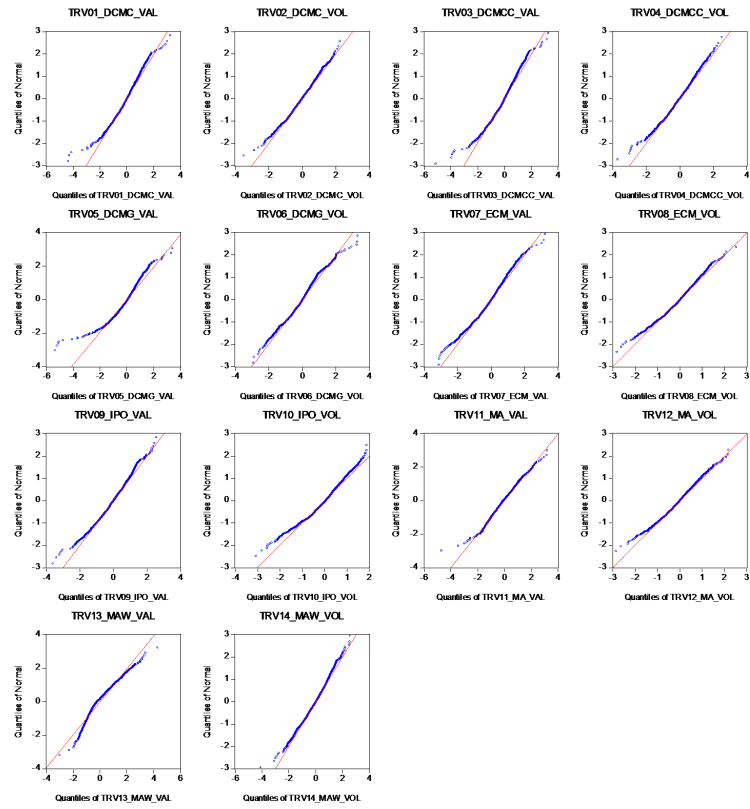
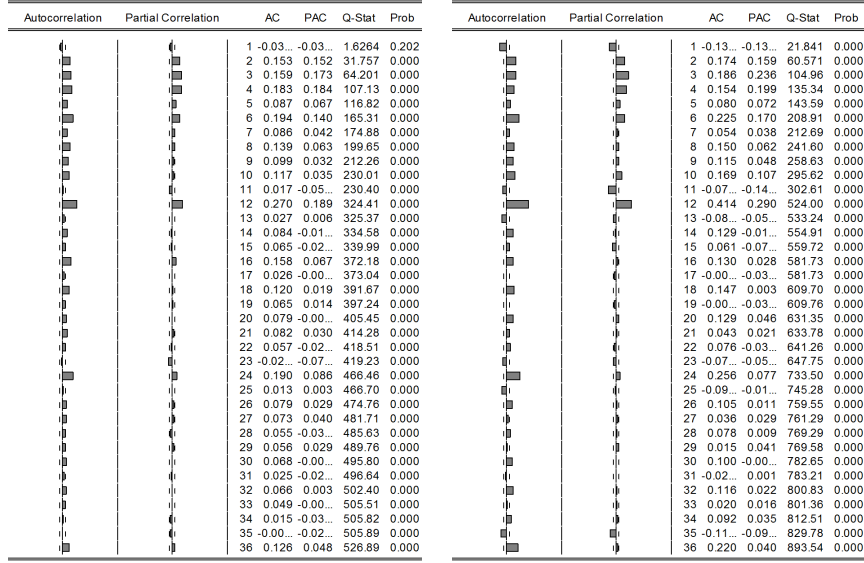
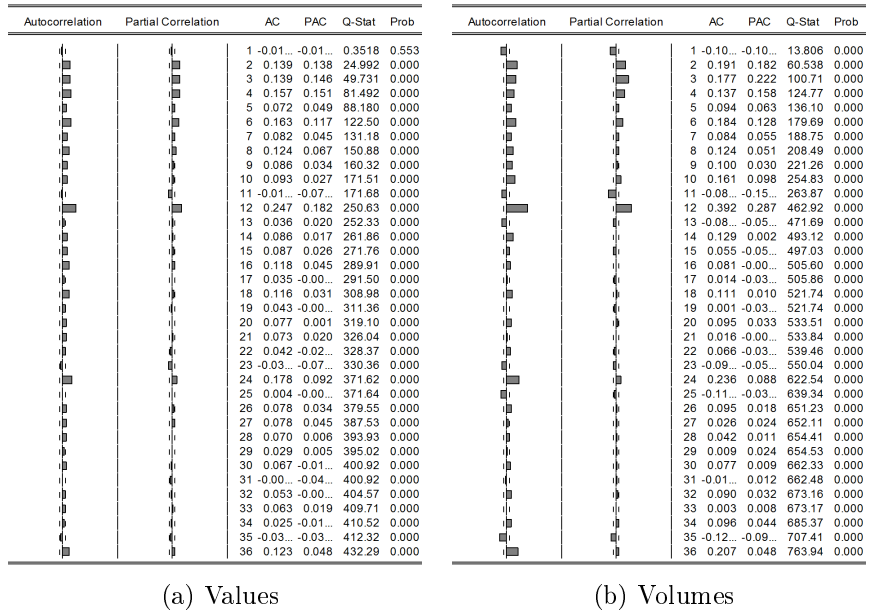


Figure 23: Residuals Diagnostics: Normality Analysis



(a) Values (b) Volumes

Figure 24: Residuals Diagnostics: Auto-Correlation Analysis - DCMC



(a) Values (b) Volumes

Figure 25: Residuals Diagnostics: Auto-Correlation Analysis - DCMCC

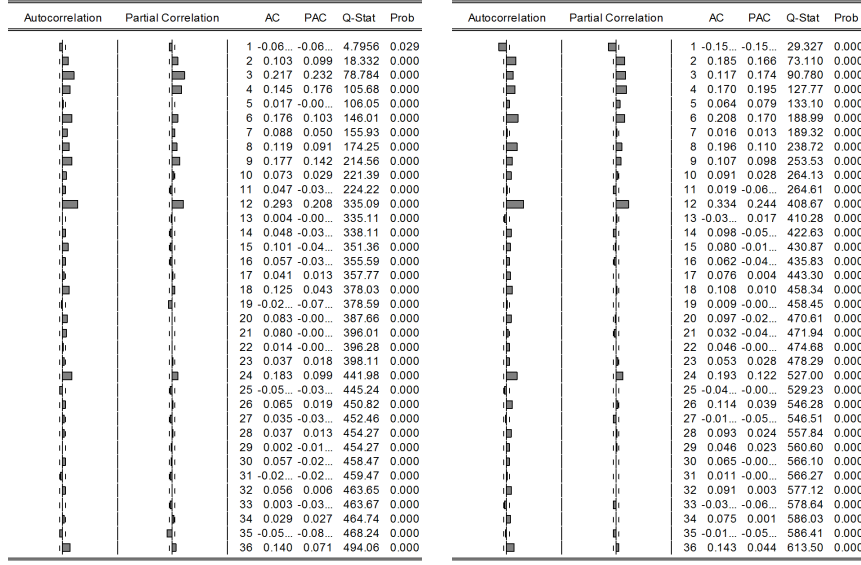


Figure 26: Residuals Diagnostics: Auto-Correlation Analysis - DCMG

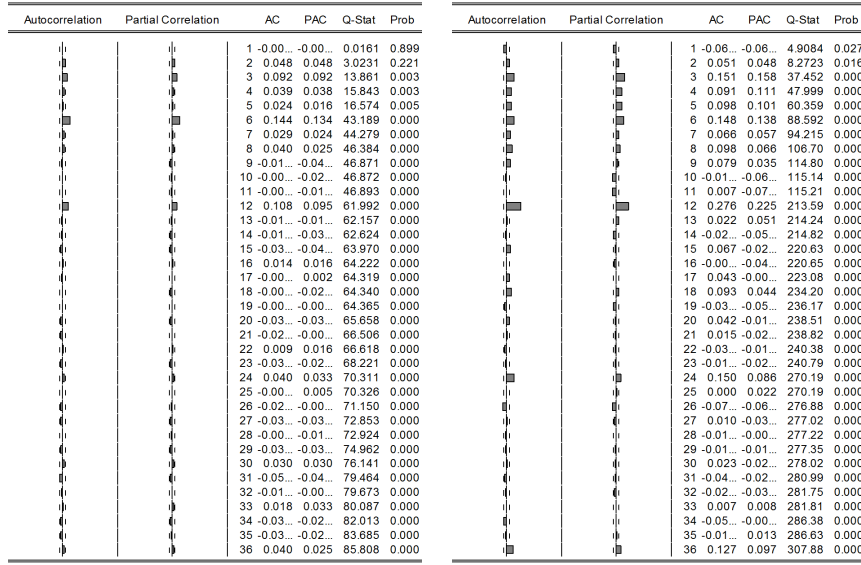


Figure 27: Residuals Diagnostics: Auto-Correlation Analysis - ECM

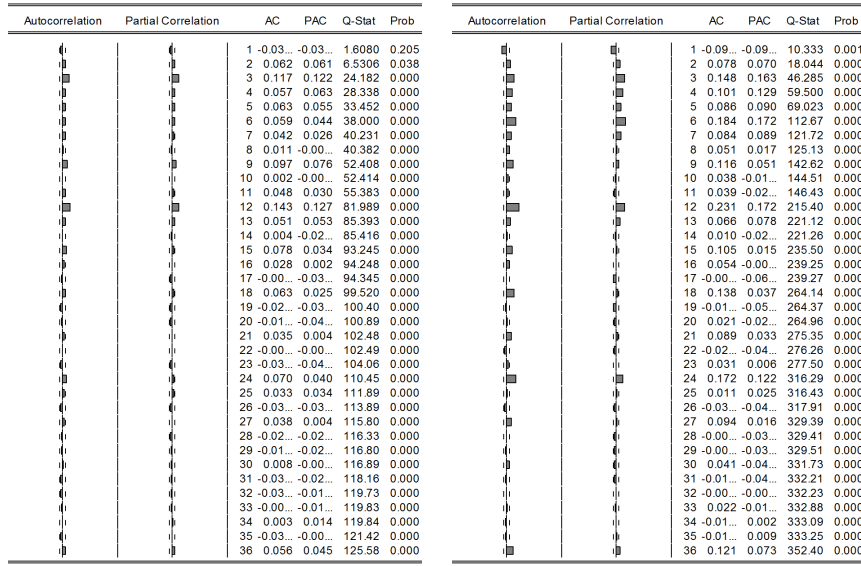


Figure 28: Residuals Diagnostics: Auto-Correlation Analysis - IPO

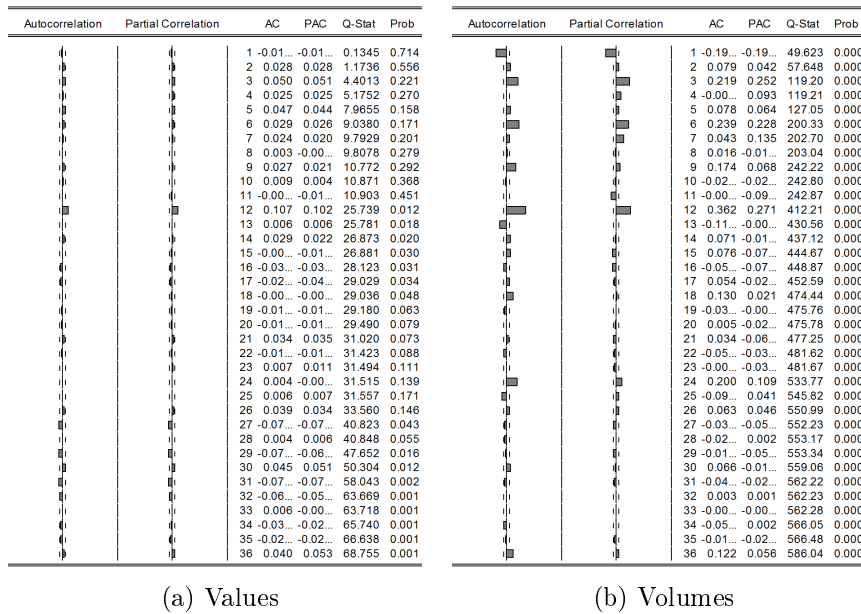


Figure 29: Residuals Diagnostics: Auto-Correlation Analysis - MA

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1	-0.01...	-0.01...	0.1448	0.704	
2	0.066	0.066	5.7421	0.057	
3	0.098	0.100	18.131	0.000	
4	0.038	0.036	19.940	0.001	
5	0.051	0.040	23.258	0.000	
6	0.050	0.038	26.449	0.000	
7	0.092	0.082	37.336	0.000	
8	0.045	0.035	39.964	0.000	
9	0.019	-0.00...	40.427	0.000	
10	0.029	0.004	41.523	0.000	
11	0.025	0.009	42.346	0.000	
12	0.037	0.024	44.113	0.000	
13	0.039	0.026	46.108	0.000	
14	0.003	-0.01...	46.119	0.000	
15	0.017	-0.00...	46.508	0.000	
16	0.056	0.046	50.563	0.000	
17	-0.02...	-0.02...	51.057	0.000	
18	0.080	0.065	59.304	0.000	
19	-0.00...	-0.02...	59.384	0.000	
20	0.053	0.040	63.066	0.000	
21	-0.01...	-0.02...	63.266	0.000	
22	0.030	0.020	64.475	0.000	
23	0.052	0.035	67.970	0.000	
24	0.015	0.011	68.273	0.000	
25	-0.02...	-0.04...	68.834	0.000	
26	0.047	0.030	71.726	0.000	
27	0.003	-0.00...	71.736	0.000	
28	-0.01...	-0.02...	71.936	0.000	
29	-0.00...	-0.02...	71.996	0.000	
30	-0.00...	-0.01...	72.024	0.000	
31	0.030	0.026	73.221	0.000	
32	0.015	0.020	73.504	0.000	
33	-0.01...	-0.01...	73.718	0.000	
34	-0.04...	-0.05...	75.964	0.000	
35	0.003	0.004	75.978	0.000	
36	-0.04...	-0.04...	78.232	0.000	

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1	-0.09...	-0.09...	12.497	0.000	
2	0.124	0.116	32.364	0.000	
3	0.125	0.151	52.424	0.000	
4	0.109	0.127	67.815	0.000	
5	0.126	0.125	86.077	0.000	
6	0.060	0.066	96.233	0.000	
7	0.074	0.036	103.22	0.000	
8	0.088	0.043	113.26	0.000	
9	0.075	0.037	120.55	0.000	
10	0.072	0.031	127.28	0.000	
11	0.043	0.000	129.67	0.000	
12	0.080	0.032	137.91	0.000	
13	0.027	-0.01...	138.83	0.000	
14	0.049	-0.00...	141.93	0.000	
15	0.045	0.008	144.61	0.000	
16	0.064	0.035	149.88	0.000	
17	0.016	-0.01...	150.20	0.000	
18	0.039	0.001	152.20	0.000	
19	0.054	0.027	156.01	0.000	
20	0.059	0.041	160.55	0.000	
21	0.061	0.045	165.38	0.000	
22	0.018	-0.00...	165.82	0.000	
23	0.109	0.075	181.27	0.000	
24	-0.00...	-0.02...	181.28	0.000	
25	0.045	0.00...	183.93	0.000	
26	0.066	0.027	189.59	0.000	
27	0.026	0.002	190.51	0.000	
28	0.045	0.002	193.13	0.000	
29	-0.00...	-0.04...	193.19	0.000	
30	0.005	-0.04...	193.23	0.000	
31	0.031	-0.01...	194.46	0.000	
32	0.027	0.011	195.42	0.000	
33	0.022	0.014	196.06	0.000	
34	-0.01...	-0.01...	196.23	0.000	
35	0.005	-0.02...	196.26	0.000	
36	-0.04...	-0.06...	198.75	0.000	

(a) Values

(b) Volumes

Figure 30: Residuals Diagnostics: Auto-Correlation Analysis - MAW

Dep. Var:	F_DCMC_VAL	F_DCMC_VOL	F_DCMC_VAL_F_DCMC_VOL	F_DCMC_VOL_F_DCMC_VAL	F_DCMC_VAL_F_DCMC_VOL	F_ECM_VAL	F_ECM_VOL	F_IPO_VAL	F_IPO_VOL	F_MA_VAL	F_MA_VOL	F_MAW_VAL	F_MAW_VOL
UIX	-0.204508 (0.0790)**	-0.232719 (0.0689)***	-0.164639 (0.0778)**	-0.238929 (0.0792)**	0.080703 (0.0445)*	-0.130651 (0.0674)*	-0.213012 (0.0729)**	-0.344677 (0.0469)***	-0.240086 (0.0443)***	-0.064586 (0.0347)*	-0.035765 (0.0333)	0.081091 (0.0616)	0.116065 (0.0505)**
LMKT	0.115565 (0.0527)**	0.017621 (0.0469)	0.136034 (0.0435)***	0.030126 (0.0523)	-0.038670 (0.0646)	0.202884 (0.0752)***	0.146227 (0.0560)**	0.179672 (0.0564)**	0.213814 (0.0284)**	0.407338 (0.0638)***	0.074977 (0.0541)	0.249342 (0.0869)***	0.130535 (0.0613)**
LGDP	-0.029987 (0.0785)	-0.028796 (0.0660)	-0.006720 (0.0954)	-0.062609 (0.0718)	0.130796 (0.1092)	-0.100634 (0.0767)	-0.112450 (0.0679)*	-0.128246 (0.0645)**	-0.173930 (0.0508)***	0.006072 (0.0474)	0.098637 (0.0359)***	0.033952 (0.0470)	-0.044063 (0.0463)
D(LR)	-0.273356 (0.0761)***	-0.208611 (0.0904)**	-0.301413 (0.0818)**	-0.265366 (0.0863)***	-0.288611 (0.1389)**	0.098495 (0.1643)	0.208619 (0.1499)	0.068688 (0.0992)	0.061953 (0.0732)	-0.228790 (0.1448)	0.119755 (0.0506)**	-0.082168 (0.1240)	0.020701 (0.0470)
LAG1	0.429767 (0.1022)***	0.635692 (0.0707)**	0.312540 (0.1041)**	0.512795 (0.0883)**	0.450778 (0.1098)**	0.185509 (0.1003)*	0.507518 (0.0885)***	0.251057 (0.0337)**	0.498503 (0.0556)**	0.178544 (0.0632)**	0.728934 (0.0551)***	0.153827 (0.0583)***	0.578732 (0.0758)***
C	-0.155698 (0.0769)**	-0.106293 (0.0619)*	-0.212871 (0.0653)**	-0.134743 (0.0845)	-0.080829 (0.1015)	0.271820 (0.0441)**	0.312466 (0.0655)**	0.301939 (0.0781)**	0.301695 (0.0653)***	0.075412 (0.0576)	0.151571 (0.0906)*	-0.097088 (0.0411)**	-0.066907 (0.0597)
DUM_Q1	0.465785 (0.1245)***	0.311947 (0.1791)*	0.589681 (0.1651)***	0.290934 (0.2650)	0.375667 (0.3305)	-0.329570 (0.1015)**	-0.551710 (0.1899)**	-0.466605 (0.0600)**	-0.576220 (0.1493)***	-0.189567 (0.1118)*	-0.112556 (0.1863)	0.204105 (0.0512)***	0.200550 (0.1287)
DUM_Q2	0.160257 (0.0849)*	0.237997 (0.0649)***	0.269928 (0.0917)**	0.351253 (0.0711)**	0.214203 (0.0846)**	-0.114383 (0.1482)	-0.146925 (0.1720)	-0.154215 (0.1864)	-0.215608 (0.1755)	0.023615 (0.0775)	-0.237529 (0.1578)	0.120309 (0.1052)	-0.078868 (0.0831)
DUM_Q3	-0.048537 (0.2055)	-0.220643 (0.1042)**	-0.049462 (0.1519)	-0.219218 (0.1139)*	-0.223942 (0.0836)***	-0.627522 (0.1367)***	-0.588467 (0.1674)***	-0.587360 (0.1165)**	-0.453756 (0.1015)***	-0.223466 (0.1351)*	-0.227253 (0.1235)*	0.031464 (0.1001)	0.042955 (0.1009)
Observations:	416	416	416	416	416	416	416	416	416	416	416	416	416
R-squared:	0.3511	0.5649	0.2576	0.4357	0.3273	0.2023	0.5140	0.3874	0.6137	0.3043	0.6785	0.0981	0.4062
F-statistic:	14.4295	34.6191	9.2527	20.5932	12.9766	6.7635	28.2043	16.8628	42.3662	11.6661	56.2717	2.9016	18.2446

Table 24: Regression Results for the 14 Series in the Quarterly Specification
*Standard Error in Brackets: *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%*

Dep. Var:	F_DCMC_VAL	F_DCMC_VOL	F_DCMCC_VAL	F_DCMCC_VO...	F_DCMG_VAL	F_DCMG_VOL	F_ECM_VAL	F_ECM_VOL	F_IPO_VAL	F_IPO_VOL	F_MA_VAL	F_MA_VOL	F_MAV_VAL	F_MAV_VOL
UIX	-0.202872 (0.0756)***	-0.236400 (0.0623)***	-0.167887 (0.0714)**	-0.241413 (0.0736)***	0.070806 (0.0484)	0.041685 (0.0667)	-0.164688 (0.0670)**	-0.221335 (0.0693)***	-0.345862 (0.0478)***	-0.235861 (0.0436)***	-0.053484 (0.0352)	-0.035506 (0.0321)	0.084362 (0.0506)**	0.126351 (0.0506)**
LMKT	0.107168 (0.0741)	0.039361 (0.0516)	0.152157 (0.0706)**	0.044705 (0.0671)	0.019361 (0.0802)	0.033512 (0.0547)	0.283472 (0.0815)***	0.192297 (0.0567)***	0.185517 (0.0505)***	0.200186 (0.0301)***	0.371922 (0.0644)***	0.074066 (0.0612)	0.234914 (0.1037)**	0.100558 (0.0629)
LGDP	-0.042357 (0.1181)	0.002892 (0.0954)	0.015988 (0.1448)	-0.041110 (0.0927)	0.219884 (0.1552)	0.474206 (0.0961)***	0.001173 (0.0689)	-0.051407 (0.0984)	-0.118658 (0.0664)**	-0.221277 (0.0803)***	-0.056122 (0.0673)	0.098284 (0.0324)***	0.013134 (0.0663)	-0.090478 (0.0450)**
D(LR)	-0.275809 (0.0734)***	-0.201912 (0.0930)**	-0.287315 (0.0810)***	-0.260951 (0.0823)***	-0.272918 (0.1304)**	-0.268513 (0.0643)***	0.117210 (0.1493)	0.220121 (0.1347)	0.088675 (0.0974)	0.052343 (0.0786)	-0.235456 (0.1386)*	0.119490 (0.0499)**	-0.085884 (0.1206)	0.011309 (0.0639)
LGDP_INV	0.023797 (0.0826)	-0.060540 (0.0693)	-0.043424 (0.1013)	-0.040459 (0.0652)	-0.155632 (0.0773)**	-0.264938 (0.0534)***	-0.197615 (0.0504)***	-0.111991 (0.0860)	-0.017681 (0.0462)	0.075441 (0.0754)	0.118177 (0.0608)*	0.002679 (0.0269)	0.039811 (0.0574)	0.087356 (0.0431)**
C	-0.157874 (0.0749)**	-0.100632 (0.0638)	-0.208988 (0.0629)***	-0.130873 (0.0873)	-0.074835 (0.1035)	-0.020819 (0.1361)	0.283072 (0.0435)***	0.323161 (0.0886)***	0.303715 (0.0764)***	0.284152 (0.0823)***	0.064058 (0.0539)	0.151325 (0.0902)*	-0.100424 (0.0429)**	-0.074875 (0.0603)
DUM_Q1	0.469360 (0.1236)***	0.302923 (0.1860)	0.582975 (0.1679)***	0.284868 (0.2709)	0.354344 (0.3370)	0.106256 (0.3493)	-0.352527 (0.1109)***	-0.572926 (0.2026)***	-0.469932 (0.0581)***	-0.557881 (0.1492)***	-0.168424 (0.1127)	-0.112097 (0.1860)	0.210316 (0.0483)***	0.215546 (0.1313)
DUM_Q2	0.163154 (0.0815)**	0.230938 (0.0672)***	0.265488 (0.0886)***	0.346486 (0.0718)**	0.210736 (0.0857)**	0.194774 (0.0964)**	-0.128475 (0.1507)	-0.157418 (0.1695)	-0.155952 (0.1858)	-0.211199 (0.1728)	0.035370 (0.0767)	-0.237243 (0.1568)	0.124299 (0.1035)	0.002226 (0.0848)
DUM_Q3	-0.047064 (0.2027)	-0.225162 (0.1038)**	-0.051568 (0.1507)	-0.222594 (0.1150)*	-0.219317 (0.0824)***	-0.196226 (0.1509)	-0.627735 (0.1291)**	-0.596642 (0.1693)***	-0.588776 (0.1161)***	-0.447070 (0.0995)***	-0.214773 (0.1239)*	-0.227119 (0.1239)*	0.033338 (0.1026)	0.047620 (0.0882)
LAG1	0.427770 (0.1011)***	0.641109 (0.0725)***	0.313471 (0.1060)**	0.516535 (0.0811)***	0.425466 (0.1212)**	0.337120 (0.1025)***	0.168721 (0.0980)*	0.519153 (0.0863)***	0.253084 (0.0356)***	0.470756 (0.0565)***	0.162853 (0.0656)**	0.726755 (0.0520)***	0.151906 (0.0553)***	0.569409 (0.0753)***
Observations:	416	416	416	416	416	416	416	416	416	416	416	416	416	416
R-squared:	0.3514	0.5666	0.2585	0.4365	0.3388	0.4405	0.2213	0.5200	0.3875	0.6160	0.3110	0.6785	0.0989	0.4098
F-statistic:	13.5093	32.5999	8.6928	19.3164	12.7792	19.6363	7.0689	27.0147	15.7790	40.0112	11.2553	52.6237	2.7363	17.3170

Table 25: Regression Results for the 14 series in the Quarterly Specification with Investments Series added
*Standard Error in Brackets: *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%*

Dep. Var:	F_DCMC_VAL	F_DCMC_VOL	F_DCMCC_VAL	F_DCMCC_VO...	F_DCMG_VAL	F_DCMG_VOL	F_ECM_VAL	F_ECM_VOL	F_IPO_VAL	F_IPO_VOL	F_MA_VAL	F_MA_VOL	F_MAV_VAL	F_MAV_VOL
UIX	-0.21015 (0.0807)***	-0.231929 (0.0704)***	-0.16891 (0.0786)**	-0.23736 (0.0834)***	0.091251 (0.0470)*	0.057583 (0.0652)	-0.130750 (0.0719)*	-0.196999 (0.0769)**	-0.355919 (0.0471)**	-0.235370 (0.0467)***	-0.075218 (0.0358)**	-0.046950 (0.0355)*	0.075867 (0.0677)	0.108068 (0.0535)**
LMKT	0.106950 (0.0546)*	0.018653 (0.0538)	0.129823 (0.0514)**	0.031816 (0.0562)	-0.022778 (0.0666)	-0.059012 (0.0686)	0.202724 (0.0728)***	0.170142 (0.0543)***	0.164559 (0.0527)***	0.219265 (0.0263)***	0.391587 (0.0738)***	0.058198 (0.0574)	0.241545 (0.0894)***	0.119060 (0.0657)*
LGDP	-0.028742 (0.0789)	-0.028926 (0.0669)	-0.005887 (0.0955)	-0.062787 (0.0721)	0.128972 (0.1095)	0.299422 (0.0681)***	-0.100614 (0.0754)	-0.115136 (0.0649)*	-0.126822 (0.0664)*	-0.173949 (0.0507)***	0.008127 (0.0486)	0.101977 (0.0365)***	0.034907 (0.0477)	-0.042691 (0.0460)
D(LR)	-0.267648 (0.0848)***	-0.209247 (0.0940)**	-0.287364 (0.0877)***	-0.266439 (0.0895)***	-0.298894 (0.1422)**	-0.297077 (0.0687)***	0.098592 (0.1673)	0.194217 (0.1438)	0.097154 (0.1030)	0.057746 (0.0736)	-0.216767 (0.1480)	0.130900 (0.0490)***	-0.076975 (0.1273)	0.028023 (0.0472)
D(F_LOANS)	0.168942 (0.3495)	-0.019688 (0.2635)	0.116553 (0.4511)	-0.031013 (0.3152)	-0.283723 (0.3371)	-0.017475 (0.3210)	0.002703 (0.3151)	-0.430578 (0.1859)**	0.289738 (0.1985)	-0.123525 (0.1115)	0.331362 (0.2298)	0.311237 (0.2236)	0.144344 (0.2131)	0.193832 (0.2587)
C	-0.168738 (0.1006)*	-0.104766 (0.0665)	-0.221660 (0.0854)***	-0.132378 (0.0847)	-0.059587 (0.1063)	-0.026172 (0.1412)	0.271624 (0.0453)***	0.344754 (0.0878)***	0.279763 (0.0726)***	0.311088 (0.0895)***	0.050035 (0.0481)	0.128075 (0.0931)	-0.107963 (0.0421)**	-0.081216 (0.0705)
DUM_Q1	0.465971 (0.1250)***	0.311930 (0.1797)*	0.589882 (0.1633)***	0.290883 (0.2660)	0.375055 (0.3344)	0.136415 (0.3621)	-0.329575 (0.1013)***	-0.552762 (0.1838)***	-0.465185 (0.0653)***	-0.577144 (0.1497)***	-0.187991 (0.1160)	-0.111604 (0.1849)	0.204431 (0.0517)***	0.200663 (0.1291)
DUM_Q2	0.177300 (0.1014)*	0.236034 (0.0660)***	0.281590 (0.1099)**	0.348247 (0.0915)**	0.187396 (0.0984)*	0.199830 (0.0830)**	-0.114134 (0.1259)	-0.187607 (0.1795)	-0.126676 (0.1672)	-0.227031 (0.1815)	0.055215 (0.0667)	-0.207855 (0.1396)	0.134125 (0.1044)	0.009969 (0.0940)
DUM_Q3	-0.044194 (0.2147)	-0.221199 (0.1048)**	-0.046514 (0.1615)	-0.219899 (0.1134)*	-0.229961 (0.0897)**	-0.208292 (0.1491)	-0.627476 (0.1387)***	-0.597713 (0.1574)**	-0.580258 (0.1199)**	-0.456734 (0.0597)***	-0.2715236 (0.1317)	-0.220488 (0.1288)*	0.034656 (0.1008)	0.046824 (0.0877)
LAG1	0.426780 (0.1051)***	0.636055 (0.0699)***	0.311262 (0.1065)**	0.513060 (0.0900)***	0.450792 (0.1079)**	0.400990 (0.0929)***	0.185533 (0.0995)*	0.507902 (0.0891)***	0.248279 (0.0352)**	0.489059 (0.0556)***	0.173700 (0.0601)**	0.725749 (0.0557)***	0.152851 (0.0579)***	0.580706 (0.0729)***
Observations:	416	416	416	416	416	416	416	416	416	416	416	416	416	416
R-squared:	0.3517	0.5649	0.2579	0.4358	0.3290	0.4094	0.2023	0.5178	0.3891	0.6140	0.3066	0.6805	0.0985	0.4070
F-statistic:	13.5288	32.3752	8.6649	19.2594	12.2290	17.2658	6.3249	26.7794	15.8609	39.6704	11.0260	53.1156	2.7262	17.1152

Table 26: Regression Results for the 14 series in the Quarterly Specification with Loans Series added
Standard Error in Brackets: *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%

