Comovements in Corporate Waves[*†]

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Abstract

This paper analyzes the common factor that drives the cyclical movements in the corporate event waves. We show that this common corporate factor is closely linked to the economic business cycles. We, first, document the statistical and the time-series properties of the corporate event waves to determine the commonalities, the interdependence, and the comovements between them. We show that all the waves have similar ARMA and ARCH characteristics. Moreover, we conjecture that there are two major factors forming a corporate event wave: a systematic (or common) factor and a wave-specific (or idiosyncratic) factor. To study the common dynamics and the common factor, we propose a factor model with ARMA and ARCH properties, and develop a novel Bayesian estimation method for this model. We find that the percentages of the wave series that are driven by the common factor range from 3.54% for the IPO wave to the 67.5% for the divestitures wave. We also check whether the estimated common factor can be proxied by any major macroeconomic or financial variable. We find that the best proxy candidates are the variables closely associated with the business cycle: the industrial production (aggregate output), the inverse of the long-term interest rates (10-year T-bond yields), and the S&P 500 index (stock market levels).

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JEL Classification: C11, C32, G14, G34, G35.

I. Introduction

Corporate events, such as divestitures (DIV), initial public offerings (IPO), mergers and acquisitions (M&A), stock repurchases (REP), and seasoned-equity offerings (SEO) are a result of individual firms' decisions. However, the decision associated with each event is likely to be affected by various external factors, such as macroeconomic conditions, industry shocks, and stock market valuations. In the current literature, each of these events' time-series (or briefly waves) have been analyzed in isolation from each other,[1] but these external factors should form some commonalities between the waves. For example, all of these corporate events' time-series series are found to exhibit cyclical pattern,[2] but "What causes cyclical behavior in these events' time-series?" is still an open question.

This question is an important one for the economic policy-makers and corporate managers. It might reveal how – if they want to – policy-makers can influence these corporate event waves through monetary or fiscal policies. Similarly, corporate managers may find it useful to know what external factors create favorable conditions for enacting certain restructuring events in their firm. They can predict the formation of such an environment by observing the changes in the underlying variable(s) that cause (or that indicate ahead of time) the rise in the corresponding wave.

This study contributes toward finding the answer to this question by extracting the underlying common factor that causes the cyclical behavior in all the waves, and by showing that that it is closely associated with the business cycle. In a related analysis, we also try to understand the basic interdependence and co-movements between the waves and how this interdependence changed over time. Does the increased "heat" in one wave cause an increase in another one (Granger causality)? We determine empirically the time-variation in the degree of comovements between the waves. Understanding the changes over time in the strength of interdependence between the waves would enable us to identify the economic conditions that were prevalent during the periods of high correlations and

[1]The exceptions are the papers by Rau and Stouraitis(2007) and Dittmar and Dittmar (2008).

[2]For evidence on divestitures see Comment and Jarrell (1995), Berger and Ofek (1999), and Schlingemann, et al. (2002). For documentation of IPO cycles see, among others, Ritter (1984), Lowry and Schwert (2002), Lowry (2004), Pastor and Veronesi (2005), and Yung, et al. (2008). Some studies on M&As waves are Mitchell and Mulherin (1996), Shleifer and Vishny (2003), Harford (2005), and Rhodes-Kropf, et al. (2005). Some relevant papers in the SEO literature are Choe, et al. (1993) and Bayless and Chaplinsky (1996). Finally, for evidence on repurchases waves refer to Grullon and Michaely (2002) and Dittmar and Dittmar (2007).

thus, could guide us in understanding what is causing the event cycles.

We start by observing that the monthly dollar volume[3] of DIV, IPO, M&A, REP, and SEO activity is showing a substantial variation over time (see *Figure 1*). The sources of this volatility is not completely known to this date. In certain times the dollar volumes of these events seems synchronized, and in other times the correlation between them is quite low. Since we aim to find a systematic explanation for the cyclicality and the comovements in all the waves, we avoid any wave-specific or firm-specific reasons affecting a certain corporate event. The literature has already determined many cross-sectional (across the individual firms) causes of each wave.[4]

We, essentially, postulate that there are two types of forces that shape the pattern of each wave. First one is more systematic in nature, and it is closely related to the aggregate economy and the prevalent market conditions. We call it the *systematic* or *the common factor* forming the waves. It affects all the waves all the time, but its effects can be time-varying and cross-sectionally different across the waves. Some examples of the systematic factor could be the macroeconomic variables or the asset valuation measures. The second one is *the idiosyncratic factor* (all the *wave-* and *the firm-specific* factors), so it can not be estimated from the aggregate time-series of the events; it can only be deducted. Examples for the idiosyncratic factors can be cited as exogenous industry shocks that make certain event more value-increasing to the firm than the others, institutional changes that make it cheaper (or more expensive) to do one of the events but not the other, manager's belief that a certain restructuring will improve the firm's productivity, etc.

The common factor affecting the time series of all corporate waves must exists, because firms are part of the "big ocean" called aggregate economy. Their apparently-independent corporate decisions are likely affected by the conditions of this economy, which can be changed by various macroeconomic shocks, Government's or Federal Reserve's actions, etc. Further, these conditions should be felt by all the firms – diversifying, merging, equity issuing and so on – and thus, these conditions should form a natural commonality in the waves' time series.

[3]We explain later on in the paper the reasons for using the monthly dollar volume measure rather than monthly number of events measure, which is more common in the related literature (see Rau and Stouraitis (2007) paper).

[4]Refer to, among others, Colak and Whited (2007) for divestitures, Lowry (2003) and Pastor and Veronesi (2005) for IPOs, Eckbo and Masulis (1995) for SEOs, Jovanovic and Rousseau (2001) and Maksimovic and Phillips (2001) for M&As, and Dittmar and Dittmar (2007) for repurchases.

Also, in this paper, we suggest a methodological (or a systematic) framework for analyzing the relationship between any two corporate event waves. This method is the factor analysis. Many financial and macroeconomic activities are characterized by some common movements. The factor analysis has been the predominant choice in the economics and the financial literature to analyze these common behaviors (for some examples see Bekaert and Hodrick (1992), King et al. (1994), Dungey et al. (2000), and Kose, et al. (2003)). In our case, we do not know, *a priori*, what this common factor is. So we are confined to estimating a *latent* factor model in which the monthly IPO, SEO, DIV, REP, and M&A volume is affected by the changes in an unobservable latent variable and by a wave-specific residual variable.

To apply the factor analysis in this context, we first document – as far as we know, for the first time in the literature – the time-series characteristics (ARMA-GARCH) of these waves. Somewhat surprisingly, we find that all five corporate event waves do show similar time series properties: they all can be characterized by ARMA(1,1) and GARCH(1,1). Also for the first time in the literature, we use a novel Bayesian approach (developed for the purposes of this study) to extract the common factor driving these waves. Thus, our paper has important contributions also to the Bayesian factor analysis literature.

The novelty in our econometric approach lies in methodologically developing and empirically implementing a Bayesian method for extracting the common factor while the factor has ARMA(1,1) and ARCH(1) properties.[5] We have considered alternative econometric methods for the estimation of the factor model. The proposed common factor model can not be estimated with GMM or Kalman Filter, because of the presence of heteroskedastic conditional variances in the time series of our waves. If we employ maximum likelihood (ML) estimation, we would need to deal with expectations and their approximations. This would make the ML estimation quite complicated. Considering the complexity of the model, Bayesian estimation is easier and tractable, while its flexibility in the analysis is another advantage.

Upon extracting the common factor using our Bayesian method, we check which macroeconomic variables are the primary candidates for this common factor. After considering several such variables, we find that the best candidates are the variables closely associated with the business cycle: the industrial production (i.e. aggregate output), the inverse of the long-term interest rates (10-year T-bond yields), and the S&P 500 index

[5]We explain later on why we are confined to estimating ARCH(1) instead of GARCH(1,1).

(stock market levels). This suggests that the business cycle (and/or the stock market) are the main causes of the common cyclical movements in the corporate event waves.

We also report what percentage of each wave is driven by this common factor, and how does this percentage changed over time. We find that the DIV and the REP waves have the highest proportion of the wave explained by the systematic factor (67.50% and 65.10%, repectively). The wave that is explained the least by this systematic factor is the IPO wave (only 3.54%). Therefore, the waves that are the most dependent on the exogenous economic factor, seem to be the divestitures and the repurchases waves.

Brief outline of the remaining parts of the paper is as follows. Section II describes our data sources and the formation of our wave series. Section III reports the statistical and time series characteristics of these waves and their interactive properties. Section IV introduces a latent factor model of interdependence between these waves, and suggests a Bayesian estimation method for extracting the common factor affecting these waves. The same section also reports the results from the estimation, and tries to identify specific set of macroeconomic and financial variables that might be forming this common factor. Section V concludes and suggests further venues of research in this area.

II. Corporate Waves and Business Cycles

While both the business cycles literature in economics and the corporate events literature in finance are well developed fields, it is surprising that we still do not know the answer to a simple question like, "Roughly, what percentage of a given corporate wave can be explained by an aggregate factor, like the business cycle?" This study attempts to answer questions like this, and in doing so, it links these two literatures.

A. Relevant Corporate Waves Literature

Each five of the aforementioned corporate events has been analyzed extensively before, and the literature explaining the causes of each wave is quite extensive. However, the attempts to link these waves with each other under a common analytical theme has been a more recent phenomenon. Several alternative explanations emerged as to why these waves are so strongly interrelated.

A.1. Neoclassical Explenation

According to this explanation, changing macroeconomic and industry conditions would induce the firms to engage in various efficiency increasing and value maximizing events. Since each firm's situation is unique, and during economic expansions many variables change at the same time (uncertainty, cost of capital, cash inflows, liquidity, productivity, growth rates, capital needs, etc.), the most optimal action for a particular firm can differ from the optimal action(s) of others. Hence, we can see intense activity in several corporate events simultaneously.

Dittmar and Dittmar (2008), for example, show that, inherently opposite event waves, such as the stock repurchases wave and the stock issuances wave are highly correlated, because of economic, and not market misvaluation, reasons. Market overvaluations would have caused most of the firms to choose the equity issuance event as the most value maximizing response. Stouraitis and Rau (2009), expand their scope of analysis to five different corporate waves (new and seasoned stock issues, stock and cash-financed M&As, and stock repurchases), and also find some support for the neoclassical explanation: factors such as low unemployment, high future capital expenditures, and low cash holdings, have explanatory power over equity issuance waves.

At individual wave level, numerous studies show that various neoclassical factors explain the aggregate series of a certain corporate event. Availability in capital liquidity and relaxation of financial constraints, for example, affect divestitures (Schlingemann, et al., 2002; Eisfeld and Rampini, 2006), IPOs (Lowry, 2003), and M&As (Harford, 2005). Time varying cost of capital is associated with SEO waves (Choe, et al., 1993; Lucas and McDonald, 1990; Bayless and Chaplinsky, 1996) and takeovers (Weston, et al., 2004). GDP growth affects IPOs (Lowry, 2003), SEOs (Choe, et al., 1993), M&As (Maksimovic and Phillips, 2001), and divested assets (Maksimovic and Phillips, 2001). Finally, Stephens and Weisbach (1998) show that repurchases are procyclical.

A.2. Market Timing Explanation

This explanation suggests that firm managers undertake certain corporate event to time the over- or under- valuations in the stock market. According to this hypothesis, while some waves should peak around the same time (like, IPOs and SEOs), others should be negatively correlated (for example, SEOs and Repurchases; M&As and Divestitures). While thorough and coherent empirical analysis on how and when market misvaluations can cause *all* the major corporate waves to be positively correlated is still missing from the literature, Stouraitis and Rau (2009) present partial evidence on how SEO and IPO waves can occur simultaneously in industries with large cross-sectional dispersion of firm valuations.

Numerous studies, in contrast, have shown the effects of market valuations on the *individual* waves. M&A waves tend to coincide with rising stock markets (Rhodes-Kropf and Vishwanathan, 2005; Shleifer and Vishny, 2003; Dong, et al., 2006). Baker and Wurgler (2000) explains brisk equity issuance activity with market overvaluation and the related market timing by the managers. Graham and Harvey (2001)'s paper reports evidence of some managers believing in "window of opportunity" in equity issuance. Large number of empirical studies attribute IPO waves to investor sentiment (see, for instance, Loughran and Ritter, 1995; Rajan and Servaes, 1997; and Lowry, 2003). Finally, several recent studies attempt to link the repurchases activities to recent underperformance in the stock market (Brav, et al., 2005; Jagannathan, et al., 2007; and Peyer and Vermaelen, 2007).

A.3. Other Explanations

Various other, more random, explanations for the link between several waves can also be found in the literature. Fama and French (2001) show that the positive relationship between repurchases wave and the M&A wave can arise purely due to mechanical reasons related to how M&A activities are financed. Stouraitis and Rau (2009) point similar mechanical reasons for the relationship between equity issuances and M&A activity. Lyandres, et al. (2007) theoretically show how IPO decision may be driven by a subsequent merger strategy.

III. Data and Wave Measures

This section describes the data we use to construct our measures of the corporate event waves. We use five different event samples: one sample of firms that went through a divestiture event, second sample is constitute of firms undergoing initial public offering, third event sample is firms engaging in Mergers & Acquisitions, fourth sample of events covers firms repurchasing their stock, and the last event sample includes firms issuing seasoned equity.[6] We describe the construction of each wave separately.

A. Divestitures (DIV) Wave

We use Security Data Corporation (SDC)'s Mergers and Acquisitions Database to identify all the divestitures announced during the period from January 1^{st} 1981 to December 31^{st} 2007. Unfortunately this database does not provide reliable information about divestiture events for the years before 1981, so we start our sample in January 1981 (or briefly 1981:01). The initial sample covers 63,881 divestitures that are not subsequently withdrawn. We rely on SDC's definition of what a divestitures event is and thus, we do not perform any further sample selection criteria. However, not all divestiture observations in this initial sample have information about the "value of transaction," which is a necessary variable for us to construct our dollar-volume wave measure. Therefore, after eliminating observations with missing "value of transaction" item, we end up with a final sample of 28,390 divestitures events for the period between 1981 and 2007.

For each month in our sample period we calculate the total volume of transactions as the sum of the "value of transaction" items of all the divestitures in our final sample, with announcement dates in that particular month. Total volume of transactions is then converted to year 2000 dollars using monthly CPI data available through Bureau of Labor Statistics. We call this measure *VolDivM*. The natural logarithm of monthly observations of *VolDivM* constitutes our *divestitures wave* (briefly *LogVolDIV*). For this wave we have observation for each month between 1981:01 and 2007:12 i.e., there are no months where we have no divestiture events taking place.

B. Initial Public Offerings (IPO) Wave

We use Thompson Financial's Securities Data Company (SDC) and Jay Ritter's hand collected data (from 1975 and 1984) to construct our initial sample of IPO firms. We apply the following sample selection criteria to this initial sample. To be consistent with

[6] We chose those five event waves, because we believe they are the most commonly observed corporate events, and they are the most widely analyzed in the literature. They also can be sorted into pairs; each pair capturing two sets of opposing activities. Merging vs. divesting firms, and equity (new or seasoned) issuing vs. equity repurchasing firms. Furthermore, the availability of high frequency data for the other corporate events places major restrictions on their analysis: there are many months with no event taking place in them.

the Divestitures wave's sample period, we require that the IPO should be issued between 1981:01 and 2007:12. We eliminate REITs, closed-end funds, ADRs, MLPs, and LBO firms from the sample. We also exclude any issuance with missing proceeds information, because this variable is essential in calculating our IPO wave measure. After these filters, the SDC source yields a sample of 9,257 firms. Ritter's dataset adds 511 new IPOs not covered by SDC. Thus, our final sample consists of 9,768 initial public offerings.

The data items we extract from this database are the date of the issue and the dollar value of proceeds raised by the new public firm. In case of disagreement between the data sources about the reading in certain common observations, we use Ritter's values first and then SDC's values.

Our *IPO wave (LogVolIPO)* is constructed similarly to the divestitures wave: for each month in the sample period the total dollar volume (*VolIPOM*) is calculated as the logarithm of the sum of the proceeds of all the IPOs with announcement dates within that month, converted to year 2000 dollars. For five months in our sample period (in 2001, 2002, and 2003) we have no IPO activity, which means that for those months the IPO dollar volume is zero.

C. Mergers and Acquisitions (M&A) Wave

We use SDC's Domestic Mergers and Acquisitions database to extract our sample of M&A events between 1981:01 and 2007:12 with nonmissing information about the value of the transaction.[7] We define a transaction as an M&A event, if it is completed, and if it is classified by SDC as a merger or an acquisition of majority interest. We eliminate cross-border deals and deals involving liquidations, bankrupt firms (Chapter 11), joint ventures, or government firms. We do not distinguish between M&As with stock or with cash, but we make sure that the target's public status is not classified by SDC as a subsidiary.[8] This leaves us with a final sample of 17,545 M&A events.[9]

[7] To be consistent with Divestitures sample, we start M&A sample period at 1981:01, as well.

[8] In some instances the divested subsidiary may also be counted as an M&A by SDC. By excluding the targets that are subsidiary of another firm, we assure that there is no overlapping between DIV and M&A waves.

[9] Our definition of an M&A event is different from the descriptions of M&As in Rau and Stouraitis (2008)' paper. We consider an M&A transaction to be an event that is only between two stand-alone firms. They include tender offers, LBOs, acquisition of partial or minority interest, and divestiture events to their M&A sample. We consider divestitures to be a reciprocal event to an M&A event: first one is

Using this sample we form our *M&A wave* (or *LogVolMA*) by adding the values of all the M&A transactions announced within a given month (expressed in year 2000 dollars) and then taking the natural logarithm of the sum. For all the months within the sample period we have at least one M&A event taking place, so we have no missing monthly observations for this wave.

D. Stock Repurchases (REP) Wave

From SDC's Domestic Mergers and Acquisitions database we obtain our raw sample of 20,793 buybacks (repurchases + self-tender offers) announced between 1981:01 and 2007:12. We eliminate observations that involve liquidations, joint ventures, limited partnerships, LBOs, or government firms. We also make sure that the deals do not belong to firms that are subsidiary of another firm, that they are not later on withdrawn, and that they do not have missing value of transaction. This leaves us with a final sample of 18,434 REP events.

Using this sample we form our *REP wave* (or *LogVolREP*) by adding the dollar values (in year 2000 dollars) of all the REP transactions announced within a given month, and then taking the natural logarithm of the sum. All the months in our sampled period have REP events in them.

E. Seasoned Equity Offerings (SEO) Wave

Data on seasoned equity issuance is from the SDC's New Issues database. We concentrate only on U.S. common stock issues announced between 1981:01 and 2007:12. Again, we exclude all the unit and the rights offers, and all the issuances by REITs, ADRs, MLPs, and closed-end funds. We also eliminate all the private placements and all the observations with missing proceeds data. We do not eliminate any offerings that belong to the same firm for the same year, as is commonly done in the SEO literature. We believe that such proximity of events does not cause a problem for our analysis. The remaining sample of SEO events with nonmissing proceeds data item is 10,743.

The *SEO wave* (or *LogVolSEO*) is measured as the natural logarithm of total proceeds raised from all SEOs issued within a given month. Again, all the dollar amounts are

an action showing the desire of a firm to get rid of some businesses, and the second one is a transaction that combines some businesses. So, we analyze two distinct event waves: a wave capturing the divesting actions and a wave representing the merging events.

converted to year 2000 dollars using monthly CPI data. None of the months in our sample period have missing observations of the SEO wave measure.

Figures 1A through *1E* depict the plot of these five waves over time.

IV. Statistical and Time-Series Properties of Waves

A common estimation methodology used in asset pricing literature for models with latent factor have been GMM. However, any presence of autoregressive and GARCH features in the returns data would lead to biased GMM estimates, and would require using alternative estimation methods.[10] Therefore, to determine the appropriate estimation method we need to use in this context, we first try to establish the autoregressive and volatility structure of the wave series.

Next, we present the descriptive statistics of each wave with emphasis on its volatility. We investigate the ARMA and GARCH properties of each wave. We try to determine the change over time in the strength of correlation between the waves, as well as the Granger causality estimates for each pair of investigated waves in this study. This information will be used later on during modeling of the common factor of our waves.

A. Descriptive Statistics of the Waves

We summarize the descriptive statistics of our waves in *Figures 2A-E*. These figures display the nonparametric kernel density plot of the natural logarithm of monthly dollar volume of Divestitures, IPOs, Mergers & Acquisitions, Repurchases, and SEOs. Information about the kernel plot, such as type of kernel plot, bandwidth, c-value, and approximate mean integrated square error (AMISE) are shown in the little boxes inside the graph-box. The sample statistics, such as number of observations, minimum, median, maximum, mean, standard deviation, skewness, and kurtosis are also displayed in a similar box. A fitted normal distribution is also graphed to help visualize the actual distribution of the wave volume against a backdrop of normal distribution with the same mean and variance. In one of the boxes we also show the results from the tests for normality of these volume distributions. The test results from Anderson-Darling normality test ($Pr > A\text{-}Square$),

[10]Some examples of latent factor models used in the presence of autoregressive and GARCH features are Efficient Method of Moments (EMM) (see Gallant and Tauchen (1996)) or simulated generalized method of moments (see Lee and Ingram (1991) and Duffie and Singleton (1996)).

Cramer-von Mises normality test ($Pr > W\text{-}Square$), and Kolmogorov-Smirnov normality test ($Pr > D$) are displayed.

Briefly, the wave distributions suggest that the DIV, IPO, REP, and SEO monthly volume numbers are highly non-normal. M&A wave's distribution is close to being normal. Another important observation from these figures, is the differences in variations in each wave's volume. The REP wave is the most volatile among the waves with standard deviation of monthly changes reaching 1.4301, followed by M&A and IPO waves with standard deviations of 1.1710 and 1.0717, respectively. The SEO and Divestiture waves are much less volatile both with standard deviations slightly less than 1.

Also, our unreported results show that the Augmented Dickey-Fuller Tests[11] and the Phillips-Perron tests applied to our wave series reject with 5% confidence the null hypothesis of non-stationarity for the series with drift and with drift and time trend. The only version of this test that we can not reject is when we assume that the mean of our wave series is zero. Since it is unrealistic (economically speaking), to assume that DIV, IPO, M&A, REP, and SEO series would have zero activity in a given month, we conclude that more relevant versions of Augmented Dickey-Fuller test are the tests with drift and/or with drift and time trend. Thus, as an important characteristics of our wave series, we establish that they are stationary with non-zero mean and/or with drift, which is essential for the analyses that will follow. Another implication is that we should not worry about "spurious regression" results usually seen in nonstationary series (Granger and Newbold (1974)). Since the waves series are stationary, we did not test for cointegration among those series.

B. Autoregressive and Heteroskedastic Properties of Each Wave

It is essential for us to establish what are the ARMA and GARCH properties of our wave series, because we will use these properties later on to create a model of waves. However, at the current stage of the literature, we have no *theoretical* arguments suggesting why the data generating process of the waves should have a certain ARMA and/or certain

[11] The three unit root (or non-stationarity) tests as suggested by Dickey and Fuller (1979) are conducted as follows. 1) Zero mean: the equation is $\Delta w_t = (\rho - 1)w_{t-1} + e_t$; 2) with drift: the equation is $\Delta w_t = \mu_0 + (\rho - 1)w_{t-1} + e_t$; and 3) with drift and time trend: the equation is $\Delta w_t = \mu_0 + \mu_1 t + (\rho - 1)w_{t-1} + e_t$. For all three versions of the test the null hypothesis is $H_0{:}\rho = 1$, and the alternative hypothesis is $H_1{:}|\rho| < 1$. The critical values for the changed distribution are as suggested by their study.

conditional heteroskedasticity features. Thus, we have to rely on statistical inference obtained from the data.

B.1. ARMA Properties

What are the ARMA properties of our waves? Durbin-Watson tests strongly rejects the null hypothesis of no autocorrelation (for all the series the p-value for testing positive autocorrelation is less than 0.01%). Further, we use a combination of Box-Jenkins approach (ACF and PCF), SCAN and ESCAF approach of Tsay and Tiao (1984, 1985), and MINIC (minimum Bayesian information criteria) to time series modeling, and we conclude that our waves are most likely to follow an ARMA process rather than an MA or an AR process.

Using Box-Jenkins approach we observe that both the autocorrelations and partial autocorrelations tapper off (another confirmation that we are dealing with stationary series). The autocorrelations are significant for 10 lags and higher, and the partial autocorrelations do fall below the cutoff levels after 4-5 lags. This is an indication that our series could possibly have a high order AR properties. However, SCAN and ESACF approach for details of this approach) suggests that all of our series are following low order ARMA processes of the form ARMA(1,1). To confirm the last result, Bayesian MINIC has its lowest values at ARMA(1,1) estimation for DIV, M&A, and SEO waves, at ARMA(3,0) for IPO wave, and at ARMA(5,0) for the REP wave. MINIC for ARMA(1,1) for the IPO wave and for the REP wave is close second in lowness, so to have some commonality among the series, which is necessary for us to build the common factor in the latent factor model, we conclude that ARMA(1,1) is the best fitting time series model for all of our series.[12]

To confirm the adequacy of these tentative ARMA models, we estimate the coefficients of a fitted ARMA(1,1) model for each wave. The results are presented in Table 2. The estimated coefficients are significant for all of our wave series. Furthermore, the unreported results for residual analysis does not contradict the above fitted model. Comparisons of Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) of current and extended models again implies that the most optimal time series model for our series

[12]The autocorrelation and partial autocorrelation results, smallest canonical correlation (SCAN) and extended sample autocorrelation function (ESACF) results, and MINIC results used to derive these conclusions are available upon request.

is ARMA(1,1).

B.2. GARCH properties

From *Figures 2A-E* we observe that the distribution of monthly volume levels for all five waves are non-normally distributed, and some waves have a heavier tails than normal (large kurtosis values). Furthermore, the differenced values of those waves (i.e. month-over-month changes in log volume levels) plotted over time show that there is some evidence of volatility clustering (these figures are available upon request). This volatility clustering in monthly changes is most likely due to unusual activity in the corresponding DIV, IPO, M&A, REP, and SEO markets in certain overheated periods. All these are signs of heteroskedastic residuals.

To formally test for presence of ARCH effects we use Lagrange Multiplier (LM) and Portmenteau Q Tests. For all of our wave series the p-values for both LM and Q tests (through order 12) are less than 1% (i.e. p-value= 0.0001), which suggests that a very high-order ARCH model may be needed. However, as Bollerslev (1986) demonstrates, in situation where many ARCH terms are needed, GARCH model with small number of terms performs better. Thus, we fit various univariate GARCH(p,q) processes into the waves data. The estimation results suggest that the most appropriate volatility structure for DIV, IPO, M&A, REP, and SEO waves is GARCH(1,1). See the estimation results in *Table 3*. As an *ex-post* confirmation of the need for using some form of time-varying conditional volatility structure, the "persistence measure" calculated as the sum of ARCH and GARCH parameters is close to 0.9 for all five wave series.

To sum up, our empirical analysis of the data indicates that these wave series have strong ARCH features, and are best represented by GARCH(1,1) conditional variance model. Furthermore, the best description of the ARMA features of these series is ARMA(1,1). We conclude, therefore, that our wave series are quite similar and surprisingly well behaved: all are stationary, and show similar ARMA and GARCH properties.

C. Correlation Coefficients Over Time

Next, we try to assess the time-variation in the correlation between each pair of waves. Such an analysis will tell us whether the interdependence between the waves is changing over time. Do the links between waves intensifies or weakens in certain time periods?[13]

To capture the time variation in the interdependence between waves, we measure the correlation coefficients between the monthly observations (in log-volumes) of each pair of waves within a moving window of 36-months. The window moves one month at a time. As we can see from *Figures 4A-L*, the correlation coefficients between waves have shown substantial variation in time.[14]

The strength and the sign of the correlation coefficients across various wave-pairs is also very different. For DIV-M&A, DIV-REP, IPO-M&A, M&A-REP, SEO-M&A, and IPO-SEO waves, for example, it is mostly positive (albeit changing in magnitude over time). The positive correlation between IPO and SEO waves is expected: the favorable conditions to issue equity affects both seasoned and new equity in similar way. The DIV-M&A, DIV-REP, and M&A-REP graphs suggest that the periods of intense M&A activity coincide with periods of increased divesting and repurchasing activity. Apparently, when some firms start acquiring businesses, others find this environment to be suitable for unloading some businesses or for buying back some stock. The synchronization between IPO, SEO, and M&A series likely increases when the conditions are favorable for equity issuances. When the stock valuations are high, firms find it suitable to issue equity, and to use the stock for acquisitions.

However, the correlation coefficients between DIV and IPO, between DIV and SEO, between IPO and REP, and between SEO and REP can easily swing from positive to negative and vice-a-versa within a period of couple of years. Notice how the correlation coefficient between DIV and IPO moves from $+0.6$ to -0.35 within 24 months period. Clearly there is an underlying (cyclical) factor that causes these swings. Furthermore, it is interesting to observe that there are periods when the correlation between equity issuances and equity repurchases are positive. Obviously, stock market timing can not be the cause of this relationship. Most likely, at such times, some firms (eg., fast growing ones) needed to raise equity capital for investment, and other firms (eg., firms in maturing industries) had extra capital to buy back equity.

Furthermore, during certain periods we observe the positive correlation between certain pairs of waves (for example, between divestitures and equity issuances (IPOs and

[13] Even though this paper does not necessarily fully address them, the natural follow up questions would be "Why it changes over time?", "Are there factors that can account for these fluctuations?", etc.

[14] We start the period in 1984, because between 1981 and 1983 we have less than 36 months of observations.

SEOs) from 1989 to 1990)) to be very high. This can be referred as a high "contagion" period between divestitures and issuances. Intensity in one wave is spreading to the other one. While this suggests existence of an interesting dynamic between these two waves, analyzing it in further details is beyond the scope of this study.

For the purposes of this paper, however, the most important benefit from analyzing these graphs is to obtain an indirect evidence of the presence of an underlying common factor driving all the waves. This factor is likely causing the variation in the degree of correlation between the waves. In some periods, when the underlying common factor is strong, the waves move in the same direction (an thus are positively correlated). In other times, when the common factor's presence is not so strong, the waves move in their own way without high synchronization.

D. Lead-Lag Relationship Between Waves: Granger Causality

Using Granger causality concept we try to determine the lead-lag relationship (or the causation) between the waves. Namely, we want to know whether among a given pair of waves there is one that has some triggering effect on the other one? Does the past observations of one wave has a predictive power on the current values of the other one (Granger causality)?

To test whether wave w_i leads wave w_j, the following reduced form regression for up to two lags[15] is estimated:

$$w_{i,t} = \pi_0 + \pi_1 w_{i,t-1} + \pi_2 w_{j,t-1} + \pi_3 w_{i,t-2} + \pi_4 w_{j,t-2} + \xi_{i,t} \tag{1}$$

A wave w_j is said to Granger cause wave w_i, if $\pi_2 \neq 0$ or $\pi_4 \neq 0$.

To test for reverse Granger causality of wave w_i on wave w_j we estimate a similar dynamic equation:

$$w_{j,t} = \eta_0 + \eta_1 w_{j,t-1} + \eta_2 w_{i,t-1} + \eta_3 w_{j,t-2} + \eta_4 w_{i,t-2} + \xi_{j,t} \tag{2}$$

Thus, the null hypothesis of wave w_i not Granger causing wave w_j is tested by checking the significances of the coefficients η_2 and η_4 (i.e., $H_0 : \eta_2 = 0$ and $\eta_4 = 0$.)

[15]We considered higher order lags, but we found that they are insignificant for most pairs of waves considered.

The results for estimating the above equations are presented in *Table 4*[16]. We present only the relevant coefficients, their p-values, and Wald (p-values) for presence of Granger causality effects. The null hypothesis for Wald test is that there is no Granger causality between given pair of waves. The coefficients' significance and Wald test results show that three clear and highly significant bivariate causality relationships emerge: 1) SEO wave seems to Granger cause (or trigger) IPO wave, but the reverse is not true; 2) SEO wave also Granger causes M&A wave, but again the opposite is not true; 3) M&A wave seems to Granger cause IPO wave; reverse is not true; 4) M&A wave leads Divestitures wave; the reverse Granger causation is significant only for the second lag if DIV; and 5) DIV seems to ignite REP, and REP has lesser causation affect on DIV. The Granger causality tests for all the other pairs of waves is insignificant and thus, inconclusive about the possible lead-lag effects between these waves.

The above three significant Granger causality results are quite interesting and open for more detailed investigation. One interpretation is that apparently SEO market serves as a trigger to both IPO and M&A markets. It is first to become active and it leads the other two. The rise in SEO issuance volume (Granger) causes M&A and IPO volume to rise (estimated coefficients are positive and significant). The relationship between M&A and SEO markets can be explained by the heavy use of equity (issuance of seasoned equity) in many acquisitions. The trigger effect that SEO market has on IPO market is surprising, though. It suggests that the first group of companies that are taking advantage of improving economic conditions and rising stock prices is the seasoned companies as opposed to new and incoming firms i.e., current public companies are the first to ignite equity capital raising spree and IPOs follow one month behind (one lagged coefficient π_2 for Eqn. 1 between IPO and SEO waves is positive and significant).

Another interesting relationship that arises from the above results is between diversification (Mergers & Acquisitions) and refocusing activities (Divestitures) of the firms. The Granger causality results suggest that M&A wave is first to heat up, and then divestiture activity starts to rise (the corresponding coefficient is positive and significant). Considering that in many cases divestitures are actually an acquisition activity by an-

[16] Similar dynamic equations are used to test for bivariate Granger causality (or linkages) between currency and equity markets in a study by Granger, et al. (2002). For robustness check we also test for Granger causality using more traditional methods such as vector autoregression (VAR) and found the coefficient significances to be the same for all pairs of waves. The Wald test results we present are obtained from estimating the VAR equation.

other firm, it is not that surprising that many would-be divesting parent firms are waiting before M&A market heats up before they divest their unit(s). There is also an evidence of Divestitures wave Granger causing M&A wave with the second lag, which means that after the divestiture activity is ignited by M&As, it feeds back and causes M&A activity to increase even more. That is, DIV and M&A waves seem to feed off of each other.

Similar feedback effects exist between DIV and REP waves. While the first lag effect is significant only for DIV Granger causing REP, the second lag effects are significant in both causality regressions.

V. A Model of Interdependence Among Waves: A Factor Model with ARMA-ARCH Properties

Next, we develop a latent factor model of wave fluctuations of the type that is commonly used in the asset pricing literature (see Cochrane (1994), Campbell and Shiller (1987, 1988)), and Lee (1996), among others) and in the international contagion literature (see, for example, Bekaert and Hodrick (1992), King, et al. (1994), Dungey, et al. (2000), and Forbes and Rigobon (2002)). The use of factor models in the corporate finance literature has been limited, however. So, below we show that they can be an excellent technique to analyze two or more aggregated corporate data series.

A. Why Latent Factor Model?

Among many alternatives, latent factor models are the most suitable, because they have three distinct advantages. First, they circumvent the need to choose specific indicators to proxy economic variables affecting the waves. Unfortunately, from the pure theoretical perspective, we do not yet know the causes of wave-like behavior in DIV, IPOs, M&As, REP, and SEOs. Thus, in any estimation we can not be sure that we can account for all the right-hand side explanatory factors.

Second, any theoretically relevant factor may not be easily measurable or may be calculated with significant measurement error, which in many instances leads to misleading estimation results. Typical example of such discrepancy between a theoretical concept and its "best" known proxy is Tobin's q. Erickson and Whited (2002) show that the best known measures of Tobin's q typically cary with them a large measurement error, which

Table 1: Testing: The Factor Model

Log Likelihood	D.F.	Statistic	P-Value
-1.54	6	377.45	0.00

Test results for the appropriateness of the factor model. The null hypothesis is the zero-factor model.

leads to misleading investment-q regression estimation results.

Finally, various econometric issues arise in situations where proxy variables are used. Endogeneity or missing variables problem can contaminate the estimation results. Besides the large econometric theory literature on the issue, there are many examples where various authors show how in specific empirical estimation context endogeneity between the proxy variables could lead to faulty economic conclusions, if in the estimated econometric model it is not properly treated for (for recent examples see Villalonga (2004) and Colak and Whited (2007)).

B. Preliminary Analysis

Before we proceed with our factor model, we first need to test whether factor modeling would be a good approach for analyzing the data. Applying the test due to Bartlett (1954), we check if a factor model is a good fit to the data. The results from this likelihood ratio test are provided in Table 1. They indicate that the factor model is highly preferred against a non-factor model. Another issue is determining the number of factors that should be employed in the model. Applying the method proposed by Bai and Ng (2002), we end up with one factor model. The number of factors should be less than $(N-1)/2$ where N is the size of the cross-sectional data. In our case $N = 5$, because we have five time series. Therefore, we should use one factor model in analyzing the common dynamics.

C. The Factor Model

The statistical properties of the wave series identified in the previous section are key in determining the appropriate estimation model we use in this section. All wave series display ARMA(1,1) and univariate ARCH (1) properties, and thus it seems like these

ARMA and ARCH structures are common across all waves. In light of these observations we model these series by using a common (latent) factor structure, whose dynamics are specified as ARMA(1,1) and ARCH(1).

Specifically, we develop a Bayesian method for the estimation of a factor model with ARMA-ARCH properties. The Bayesian estimation of a factor model with AR process is proposed by Otrok and Whiteman (1998), the Bayesian estimation of a regression with ARMA process is considered by Chib (1995), and the Bayesian estimation of a regression is developed by Nakatsuma (2000); however the Bayesian estimation of a factor model with ARMA-ARCH properties (or for that matter, ARMA-GARCH properties) is missing in the literature. So, the estimation we propose is unique in the sense that it is developed here for the first time in the literature. Our Biasian method essentially applies a hybrid method for the Markov Chain Monte Carlo (MCMC) method. That is, to generate a Monte Carlo sample from the joint posterior distribution, we employ a Markov chain sampling with Gibbs and Metropolis-Hastings algorithm together.

The MCMC method is a Monte Carlo integration method to generate samples of parameters of the model from their joint posterior distribution by Markov Chain sampling. These samples are used to compute multiple complicated integrals by Monte Carlo integration, a popular procedure in many recently developed Bayesian methods. The Gibbs algorithm and the Metropolis-Hastings algorithm are two widely used Markov chain sampling schemes in the literature. Since direct sampling from the posterior distributions of our model parameters is not possible, we employ these two powerful Markov chain algorithms in our Bayesian method for the estimation of the factor model with ARMA-ARCH processes.

Now, we begin the detailed description of the model with the evolution of our five waves as a dynamic factor structure. Let $\mathbf{w}_t$ be the $N \times 1$ vector of observed time series, generated by a set of r unobserved common factors. Then each component of the vector of observed wave series, $\mathbf{w}_t$, can be written as a linear combination of these common factors:

$$\mathbf{w}_t = \boldsymbol{\mu} + \boldsymbol{\Lambda}\mathbf{f}_t + \boldsymbol{\varepsilon}_t \tag{3}$$

where $\boldsymbol{\mu}$ is $N \times 1$ vector of deterministic coefficients, $\boldsymbol{\Lambda}$ is $N \times r$ matrix of factor loadings, $\mathbf{f}_t$ is $r \times 1$ vector of factors and $\boldsymbol{\varepsilon}_t$ is $N \times 1$ vector of idiosyncratic components.

In some instances, for the sake of simplicity, the latent factors are assumed to be a latent stochastic process with zero mean and unit variance $\mathbf{f}_t \sim iid(\mathbf{0}, \mathbf{1})$ or $\mathbf{f}_t = \mathbf{f}_{t-1} + \boldsymbol{\epsilon}_t$, where $\boldsymbol{\epsilon}_t$ is a stationary and independent disturbance term. However, in our case this factor modeling would be unrealistic. We are dealing with waves that are measured as logarithm of monthly dollar volume i.e., the mean is not zero; and as previously documented, our waves show strong ARMA and ARCH properties. Thus, the evolution of each factor, $j = 1, ..., r$, is governed by an autoregression of order p and moving average of order q:

$$f_{jt} = b_{j0} + \sum_{s=1}^{p} b_{js} f_{j,t-s} + \sum_{s=1}^{q} c_{js} e_{j,t-s} + e_{jt} \tag{4}$$

where roots of $(1 - \sum_{s=1}^{p} b_s L^s) = 0$ lie outside the unit circle.

Idiosyncratic errors in Eqn. 3 are all assumed to be normally distributed:

$$\boldsymbol{\varepsilon}_t \overset{i.i.d.}{\sim} N(\mathbf{0}, \mathbf{D}) \tag{5}$$

where $\mathbf{D} = diag(d_1, ..., d_N)$. However, the heteroskedastic variance properties are captured by the factor innovations. That is, the ARCH effects are defined as

$$e_{jt} \sim N(0, \sigma_{jt}^2) \tag{6}$$

$$\sigma_{jt}^2 = \alpha_{j0} + \sum_{s=1}^{k} \alpha_{js} e_{j,t-s}^2. \tag{7}$$

where the ARCH model coefficients have to satisfy the condition that $\boldsymbol{\alpha}_j \gg \mathbf{0}$ where $\boldsymbol{\alpha}_j = (\alpha_{j0}, \alpha_{j1}, ..., \alpha_{jk})'$. Moreover, $\boldsymbol{\varepsilon}_t$ and $\mathbf{e}_{jt}$ are mutually uncorrelated for all t.

In practice, we impose at least two sets of important constraints on parameters in the ARMA-ARCH model. First set of constraints is about the ARMA parameters:

1. All roots of $(1 - \sum_{s=1}^{p} b_{js} L^s) = 0$ lie outside the unit circle.
2. All roots of $(1 - \sum_{s=1}^{q} c_{js} L^s) = 0$ lie outside the unit circle.

These two constraints are imposed to ensure the stationarity and invertibility of the ARMA process. The second set of constraints are about the ARCH parameters:

1. For all $s = 0, 1, ..., k : \alpha_s > 0$.

This guarantees that the conditional variance σ_{jt}^2 is always positive.

The ARCH(k) structure can also be written as an AR(p) model in the following form

$$e_{jt}^2 = \alpha_{j0} + \sum_{s=1}^{k} \alpha_{js} e_{j,t-s}^2 + \omega_{jt} \tag{8}$$

which is proposed by Bollerslev (1986). Here we set $\omega_{jt} = e_{jt}^2 - \sigma_{jt}^2$. Notice that $\omega_{jt} = (\frac{e_{jt}^2}{\sigma_{jt}^2} - 1)\sigma_{jt}^2$. So $\omega_{jt} = (\chi^2(1) - 1)\sigma_{jt}^2$ is a $\chi^2(1)$ distribution multiplied by σ_{jt}^2, and therefore,

$E(\omega_{jt}) = 0$ and $Var(\omega_{jt}) = 2\sigma_{jt}^4$. We apply a normal approximation as in Nakatsuma (2000). Therefore,

$$\omega_{jt} \sim N(0, 2\sigma_{jt}^4). \tag{9}$$

D. Estimating the Factors and the Parameters

The above latent factor model can not be estimated with GMM or Kalman filter because of the presence of heteroskedastic conditional variances. Maximum likelihood estimation also requires that some expectations to be replaced by their approximations. Thus, we intend to use Bayesian estimation because of its applicability and flexibility. Bayesian inference requires us to compute the posterior distributions for model parameters. In this section, we just provide a summary of the estimation method. We apply a Markov Chain Monte Carlo (MCMC) method, more specifically the Metropolis within Gibbs sampling method, for the estimation of the factors and model parameters. Here is how it is processed step-by-step:

1. Simulate the common factors from a normal posterior distribution (Kalman filter is applied).
2. Draw the factor loadings from a normal posterior.
3. Draw the variances of idiosyncratic factors from inverted gamma distributions.
4. Draw the factor autoregressive coefficients from a normal posterior.
5. Draw the factor moving average coefficients using Metropolis-Hastings algorithm.
6. Draw the ARCH parameters from a normal posterior.
7. Draw the ARCH coefficients using Metropolis-Hastings algorithm.

More details about the estimation are available in the appendix. We use Metropolis-Hastings algorithm in the steps (5) and (7) to draw the parameters from conditional posteriors, because the derivation of the closed form posterior distribution is quite difficult to achieve.

E. Estimation Results

Following the above procedure, we obtain the estimates of our common factor and the coefficients shown in Eqn. 3. The most important result for us from this estimation is the time series of the common factor that drives our waves. *Figure 4* plots this common factor over time. Notice the secular upward trend in this factor. Since our aggregate dollar volumes were already converted to year 2000 dollars, we believe this trend reflects the genuine rise in the volume of corporate events as the U.S. economy and the U.S. markets are growing.

We estimate that the average month-over-month growth of this common factor is about 0.12% during the sampling period. There are two major incidences where this factor has declined steadily: between 1988:09 and 1991:02 it declined 10% from top to bottom (or, on average, 0.35% per month), and between 2000:02 and 2003:02 the same decline was 10.73% (on average, 0.31% per month).

There are also three major bottoms that are visible in the graph of our systematic factor: in the early 1980s, the early 1990s, and the early 2000s. All three of these troughs are separated by a decade, and all of them coincide with a major economic recession (as defined by NBER). It is interesting to note also that, major stock market drops that are not associated with an economic recession have a minimal effect on the common factor. For example, the October, 1987 crash (when the S&P 500 dropped around 25%) and the September-October, 1998 decline due to the LTCM debacle (when the S&P 500 dropped almost) are just a blip in the overall trend of the common factor. This lead us to conclude that these events do not seem to have a permanent effect on the common factor and on the corporate wave series.

In another result, we estimate the percentage of our wave series that are explained by our systematic factor. Such an analysis will tell us which of our waves have a big wave-specific component i.e., it is driven by our systematic factor to a lesser extend. It turns out that divestitures and repurchases are the corporate events that have high percentage of their series formed by our common factor (67.50% and 65.10%, correspondingly). The equity issuances (IPOs and SEOs) and the M&As have less than 50% of their values explained by the systematic factor (3.54%, 16.75%, and 46.19%, correspondingly).

E.1. The Common Factor and the Macroeconomic Variables

Next, we consider several macroeconomic variables and try to determine which of those variables could have played a major role in forming the common factor. The variables we consider are: industrial production (i.e. aggregate output), M1 money supply, 90-day T-bill rate (short-term rates), 10-year T-bond yield (long-term rates), euro-dollar parity (exchange rates), S&P 500 index (stock market), and consumer price index (CPI).

We find that among these variables, the ones that have the highest significant positive correlation with our common factor are the industrial production (correlation=+0.8563) and the S&P 500 stock index (correlation=+0.8337). The common factor and the long-term interest rates are significantly negatively correlated (correlation=-0.8393). These three macro-variables seem to have the closest relationship to our common factor.

These results suggest that the most likely cause of the cyclicality in our corporate waves is the underlying macro factors that define the business cycle. We document that the aggregate output, the stock market levels, and the long-term interest rates are the variables that are most closely related to our estimated systematic factor, which means that the business cycle is the most important cause of the genuine cyclical movements in the corporate event waves.

In the previous subsection, we also found that, while all the waves are affected by the common factor (or the business cycle), the magnitude of the effect varies from wave to wave. Therefore, we conclude that among the five waves we analyze, the divestitures and the repurchases waves seem to be affected the most from the business cycles (more than 65%). The cyclicality in the IPO and SEO waves seem to be driven to a lesser extend by this common factor, which suggest that these waves are affected by other, more numerous, factors beyond just the business cycle.

VI. Conclusion

For the first time in the literature we show that there are common and wave-specific factors that form the waves of the five different corporate events: DIVs, IPOs, M&As, REP, and SEOs. To extract the common factor we develop and estimate a novel Bayesian factor analysis model. This approach extracts a common factor with ARMA (1,1) and ARCH (1) features from several time series. With this methodology we are able to determine what percentage of each wave is driven by the common factor and what percentage by the idiosyncratic factors. Having this common factor in hand, we then determine which economic and/or market variables are most closely related to it. It turns out that the industrial production, the stock market, and the interest rates are the variables most associated with this factor.

We also report on these waves' statistical and time-series properties: their volatility and stationarity, the Granger causalities between them, and the time-variation in the correlation coefficients between them.

The study does not attempt to find all the economic factors that cause the fluctuations in the waves, nor does it attempt to determine what specifically are the channels through which the waves influence each other (i.e. channels of contagion). However, we believe that developing the framework for empirically analyzing these waves' time-series is the best foundation for the future research in the field.

There is a need for future research that would analyze a plethora of macro variables to determine the lead-lag relationship between the factor and these macro variables. Such an analysis can pinpoint which macro variables can serve as leading indicators to major changes in this common factor, which in return would cause significant fluctuations in the volume of these corporate events.

A different follow up analyzes could try to understand why in certain period commonalities between the waves is rising and during other times the waves are less integrated. Why some waves are affected differently from the common factor, i.e. why some waves have higher/lower percentage determined by the common factor?

Finally, a future work could concentrate on developing different methodologies to extract the common factor. Better macroeconomic proxies of the common factor can be proposed. Pairwise analysis of the waves, M&A vs. DIV or equity issues vs. equity repurchases, could yield new and interesting conclusions, also.

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Appendix

We derive the posterior distributions and give the details of the MCMC sampling procedure.

The kernel of the posterior p.d.f. $p(\mathbf{D}, \mathbf{\Lambda}, \mathbf{F}, \mathbf{B}|\mathbf{W})$ is proportional to the full joint distribution which is the multiplication of the prior densities and the observables density:

$$p(\mathbf{D}, \mathbf{\Lambda}, \mathbf{F}, \mathbf{B}|\mathbf{W}) \propto p(\mathbf{D})p(\mathbf{\Lambda})p(\mathbf{F}|\mathbf{B})p(\mathbf{B})p(\mathbf{W}|\mathbf{D}, \mathbf{\Lambda}, \mathbf{F}) \tag{10}$$

The full joint distribution is expressed as:

$$\begin{aligned}
p(\mathbf{W}, \mathbf{F}, \mathbf{D}, \mathbf{\Lambda}) &= p(\mathbf{\Lambda})p(\mathbf{D})p(\mathbf{F})p(\mathbf{W}|\mathbf{\Lambda}, \mathbf{D}, \mathbf{F}) \\
&= (2\pi)^{-TN/2}|\mathbf{D}|^{-\frac{T}{2}}.exp\{-\frac{1}{2}\sum_{t=1}^{T}(\mathbf{w}_t - \mathbf{\Lambda}\mathbf{f}_t)'\mathbf{D}^{-1}(\mathbf{w}_t - \mathbf{\Lambda}\mathbf{f}_t)\} \\
&\times \prod_{j=1}^{r}\prod_{t=1}^{T}(2\pi\sigma_t^2)^{-1/2}exp\{-\frac{1}{2\sigma_t^2}(f_{jt} - b_{j0} - b_{j1}\sum_{s=1}^{t}(-c_{j1})^{s-1}f_{j,t-s} + \sum_{s=1}^{t}(-c_{j1})^{s}f_{j,t-s})^2\} \\
&\times \prod_{t=1}^{T}(2\pi\sigma_t^2)^{-1/2}exp\{-\frac{1}{2\sigma_t^2}(e_{jt}^2 - \alpha_{j0} - \sum_{s=1}^{k}\alpha_{js}e_{j,t-s}^2)^2\}\prod_{i=0}^{k}I_{(0,\infty)}(\alpha_{ji}) \\
&\times (2\pi)^{-[r(2N+1-r)/2]/2}|\underline{\mathbf{H}}_\lambda|^{1/2}exp\{-\frac{1}{2}(\boldsymbol{\lambda} - \underline{\boldsymbol{\lambda}})'\underline{\mathbf{H}}_\lambda(\boldsymbol{\lambda} - \underline{\boldsymbol{\lambda}})\}\prod_{i=1}^{r}I_{[0,\infty)}(\lambda_{ii}) \\
&\times 2^{\sum_{i=2}^{N}\underline{\nu}_i/2}exp\{-\sum_{i=1}^{N}\underline{s}_i^2/(2d_i)\}\prod_{i=1}^{N}[\Gamma(\underline{\nu}_i/2)]^{-1}(\underline{s}_i)^{\underline{\nu}_i/2}(d_i)^{-(\underline{\nu}_i+2)/2} \\
&\times \prod_{j=1}^{r}(2\pi)^{-(p+1)/2}|\underline{\mathbf{H}}_B|^{1/2}exp\{-\frac{1}{2}(\mathbf{B}_j - \underline{\mathbf{B}})'\underline{\mathbf{H}}_j(\mathbf{B}_j - \underline{\mathbf{B}})\}I[s(\mathbf{B}_j)] \\
&\times \prod_{j=1}^{r}(2\pi)^{-(k+1)/2}|\underline{\mathbf{H}}_A|^{1/2}exp\{-\frac{1}{2}(\mathbf{A}_j - \underline{\mathbf{A}})'\underline{\mathbf{H}}_A(\mathbf{A}_j - \underline{\mathbf{A}})\}\prod_{i=0}^{k}I_{(0,\infty)}(\alpha_{ji}) \\
&\times (2\pi)^{-1/2}|\underline{h}_e|^{1/2}exp\{-\frac{\underline{h}_e}{2}(e_{j0} - \underline{e}_0)^2\}
\end{aligned}$$

where $\mathbf{A}_j = \{\alpha_{js}\}_{s=0}^{k}$, $\mathbf{B}_j = \{b_{js}\}_{s=0}^{p}$ and $I[s(\mathbf{B}_j)]$ is an indicator function used to denote roots of $(1 - \sum_{s=1}^{p} b_{js}L^s) = 0$ that lie outside the unit circle. We solve out the following conditional posteriors from the kernel of the full joint distribution for simulation purposes in MCMC sampling.

A couple of remarks follow about the MCMC derivations. First, we demean the data; hence we set $\boldsymbol{\mu} = 0$. Second, defining $\mathbf{\Theta} = \{\mathbf{\Lambda}, \mathbf{D}, \mathbf{F}, \mathbf{B}\}$, for notational simplicity we let $\mathbf{\Theta}_{-\theta}$ denote the set $\mathbf{\Theta}$ minus θ, where $\theta \in \{\mathbf{\Lambda}, \mathbf{D}, \mathbf{F}, \mathbf{B}\}$.

Simulating the Model Parameters

To stick with the waves results in this study, we take the ARMA(1,1) case in the following derivations and analysis. If we assume that $p = 1$ and $q = 1$, then

$$e_{jt} = f_{jt} - b_{j0} - b_{j1} \sum_{s=1}^{t} (-c_{j1})^{s-1} f_{j,t-s} + \sum_{s=1}^{t} (-c_{j1})^{s} f_{j,t-s} \tag{11}$$

for which it is worth noting that $f_{j0} = e_{j0}$. From this expression, we can deduce the posterior densities of AR and MA coefficients as well as the posterior simulation of the initial error term e_{j0}.

AR coefficients: We can rewrite this expression

$$e_{jt} = y_{jt} - b_{j0} - b_{j1} x_{jt} \tag{12}$$

where $y_{jt} = f_{jt} + \sum_{s=1}^{t} (-c_{j1})^{s} f_{j,t-s}$ and $x_{jt} = \sum_{s=1}^{t} (-c_{j1})^{s-1} f_{j,t-s}$. We know that $e_{jt} \sim N(0, \sigma_t^2)$. Therefore the kernel of $p(\mathbf{B}|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{B}})$:

$$\times \prod_{j=1}^{r} exp\{-\frac{1}{2\sigma_t^2} \sum_{t=1}^{T} (y_{jt} - b_{j0} - b_{j1} x_{jt})^2\}$$
$$\times \prod_{j=1}^{r} exp\{-\frac{1}{2} (\mathbf{B}_j - \underline{\mathbf{B}})' \underline{\mathbf{H}}_A (\mathbf{B}_j - \underline{\mathbf{B}})\} I[s(\mathbf{B}_j)]$$

We assume $\mathbf{B}_j = (b_{j0}, b_{j1})'$. The conditional posterior of $\mathbf{B}_j$ for $j = 1, ..., r$ is a multivariate normal distribution

$$\mathbf{B}_j \sim N(\overline{\mathbf{B}}_j, \overline{\mathbf{H}}_j^{-1})_{I[s(\mathbf{B}_j)]} \qquad j = 1, \ldots, r \tag{13}$$

where

$$\overline{\mathbf{B}} = (\underline{\mathbf{H}}_B + \mathbf{X}'\mathbf{X})^{-1} (\underline{\mathbf{H}}_B \underline{\mathbf{B}} + \mathbf{X}'\mathbf{Y})$$
$$\overline{\mathbf{H}}_B^{-1} = (\underline{\mathbf{H}}_B + \mathbf{X}'\mathbf{X})^{-1}$$

where $\mathbf{Y}$ is the $T \times 1$ vector of y_{jt}'s and $\mathbf{X}$ is the $T \times 2$ matrix of 1's and x_{jt}'s.

MA coefficients: Again, we can rewrite this equation as in the following form

$$e_{jt} = g_t(c_{j1}) + h_t(c_{j1}) \tag{14}$$

where $g_t(c_{j1}) = f_{jt} - c_{j1} f_{j,t-1}$ and $h_t(c_{j1}) = -b_{j0} - b_{j1} \sum_{s=1}^{t} (-c_{j1})^{s-1} f_{j,t-s} + \sum_{s=2}^{t} (-c_{j1})^{s} f_{j,t-s}$. Since $e_{jt} \sim N(0, \sigma_t^2)$, the kernel of this normal distribution as a function of MA coefficients c_{j1} is $exp\{-\frac{1}{2\sigma_t^2}(g_t(c_{j1}) + h_t(c_{j1}))^2\} = A(c_{j1})B(c_{j1})$ where $A(c_{j1}) = exp\{-\frac{1}{2\sigma_t^2} g_t^2(c_{j1}\}$ and $B(c_{j1}) = exp\{-\frac{1}{2\sigma_t^2}(2g_t(c_{j1})h_t(c_{j1}) + h_t^2(c_{j1}))\}$. Then a natural candidate proposal density for Metropolis-Hastings algorithm is $Q(c_{j1}) = A(c_{j1})$ which is a normal density. Also the target density is $P(c_{j1}) = A(c_{j1})B(c_{j1})$. Therefore, now the accept-reject function (probability of move) α is quite simple to compute:

$$\alpha = \frac{P(c_{j1}^{m+1}) Q(c_{j1}^{m} | c_{j1}^{m+1})}{P(c_{j1}^{m}) Q(c_{j1}^{m+1} | c_{j1}^{m})} = \frac{B(c_{j1}^{m+1})}{B(c_{j1}^{m})}$$

Pre-sampling error: We can put the above expression in the following form:

$$e_{jt} = f_{jt} - b_{j0} - b_{j1}\sum_{s=1}^{t-1}(-c_{j1})^{s-1}f_{j,t-s} + \sum_{s=1}^{t-1}(-c_{j1})^{s}f_{j,t-s} - b_{j1}(-c_{j1})^{t-1}f_{j0} + (-c_{j1})^{t}f_{j0}$$

which finally simplifies as

$$e_{jt} = \widetilde{y}_{jt} - \widetilde{x}_{jt}e_{j0} \qquad (15)$$

where $\widetilde{y}_{jt} = f_{jt} - b_{j0} - \sum_{s=1}^{t-1}(-c_{j1})^{s-1}[b_{j1} + c_{j1}]f_{j,t-s}$, $\widetilde{x}_t = [b_{j1}(-c_{j1})^{t-1} - (-c_{j1})^t]$ and since $f_{j0} = e_{j0}$. Hence the posterior density of the pre-sampling error is

$$e_{j0} \sim N(\overline{e}_0, \overline{h}_e^{-1}) \qquad j = 1, \ldots, r \qquad (16)$$

where

$$\overline{e}_{j0} = \underline{h}_e + \widetilde{\mathbf{X}}'\widetilde{\mathbf{X}})^{-1}(\underline{h}_e\underline{e}_0 + \widetilde{\mathbf{X}}'\widetilde{\mathbf{Y}})$$
$$\overline{h}_e^{-1} = (\underline{h}_e + \widetilde{\mathbf{X}}'\widetilde{\mathbf{X}})^{-1}$$

where $\widetilde{\mathbf{Y}}$ is the $T \times 1$ vector of $\widetilde{y}_{jt}$'s and $\widetilde{\mathbf{X}}$ is the $T \times 1$ vector of $\widetilde{x}_{jt}$'s.

ARCH coefficients: The kernel of $p(\mathbf{A}|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{A}})$:

$$\prod_{t=1}^{T} exp\{-\frac{1}{2\sigma_t^2}(e_{jt}^2 - \alpha_{j0} - \sum_{s=1}^{k}\alpha_{js}e_{j,t-s}^2)^2\}$$
$$\times \prod_{j=1}^{r} exp\{-\frac{1}{2}(\mathbf{A}_j - \underline{\mathbf{A}})'\underline{\mathbf{H}}_A(\mathbf{A}_j - \underline{\mathbf{A}})\} \prod_{i=0}^{k} I_{(0,\infty)}(\alpha_{ji})$$

We assume $\mathbf{A}_j = (\alpha_{j0}, \alpha_{j1})'$. The conditional posterior of $\mathbf{A}_j$ for $j = 1, ..., r$ is a multivariate normal distribution

$$\mathbf{A}_j \sim N(\overline{\mathbf{A}}, \overline{\mathbf{H}}_A^{-1})_{I[s(\mathbf{A}_j)]} \qquad j = 1, \ldots, r \qquad (17)$$

where

$$\overline{\mathbf{A}} = (\underline{\mathbf{H}}_A + \widehat{\mathbf{X}}'\widehat{\mathbf{X}})^{-1}(\underline{\mathbf{H}}_A\underline{\mathbf{A}} + \widehat{\mathbf{X}}'\widehat{\mathbf{Y}})$$
$$\overline{\mathbf{H}}_A^{-1} = (\underline{\mathbf{H}}_A + \widehat{\mathbf{X}}'\widehat{\mathbf{X}})^{-1}$$

where $\widehat{\mathbf{Y}}$ is the $T \times 1$ vector of e_{jt}^2's and $\widehat{\mathbf{X}}$ is the $T \times 2$ matrix of 1's and e_{jt-1}^2's.

Variance-covariance of the idiosyncratic factors: Kernel of $p(\mathbf{D}|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{D}})$:
$exp\{-\sum_{i=1}^{N}\underline{s}_i^2/(2d_i)\}\prod_{i=1}^{N}(d_i)^{-(\underline{\nu}_i+2)/2}$
$\times|\mathbf{D}|^{-\frac{T}{2}}.exp\{-\frac{1}{2}\sum_{t=1}^{T}(\mathbf{w}_t - \mathbf{\Lambda f}_t)'\mathbf{D}^{-1}(\mathbf{w}_t - \mathbf{\Lambda f}_t)\}$
$= exp\{-\sum_{i=1}^{N}\underline{s}_i^2/(2d_i)\}\prod_{i=1}^{N}(d_i)^{-(\underline{\nu}_i+2)/2}$
$\times(\prod_{i=1}^{N}d_i)^{-\frac{T}{2}}.exp\{-\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\frac{(\mathbf{w}_{it}-\mathbf{\Lambda}_i\mathbf{f}_t)^2}{d_i}\}$
$= (\prod_{i=1}^{N}d_i)^{-\frac{(\underline{\nu}_i+T+2)}{2}}.exp\{-\frac{1}{2}\sum_{i=1}^{N}\frac{\sum_{t=1}^{T}(\mathbf{w}_{it}-\mathbf{\Lambda}_i\mathbf{f}_t)^2+\underline{s}_i^2}{d_i}\}$
where $\mathbf{w}_{it}$ is the ith element of the vector $\mathbf{w}_t$ and $\mathbf{\Lambda}_i$ is the ith row of the matrix $\mathbf{\Lambda}$. So, $\frac{\sum_{t=1}^{T}(\mathbf{w}_{it}-\mathbf{\Lambda}_i\mathbf{f}_t)^2+\underline{s}_i^2}{d_i} \sim \chi^2(\underline{\nu}_i + T)$. Thus, d_i's are inverted independent gamma distribution.

Factor loadings: Kernel of $p(\mathbf{\Lambda}|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{\Lambda}})$:
$exp\{-\frac{1}{2}(\boldsymbol{\lambda} - \underline{\boldsymbol{\lambda}})'\underline{\mathbf{H}}_{\lambda}(\boldsymbol{\lambda} - \underline{\boldsymbol{\lambda}})\}. \prod I_{[0,\infty)}(\lambda_{ii})$
$\times exp\{-\frac{1}{2}\sum_{t=1}^{T}(\mathbf{w}_t - \mathbf{\Lambda}\mathbf{f}_t)'\mathbf{D}^{-1}(\mathbf{w}_t - \mathbf{\Lambda}\mathbf{f}_t)\}$
We have got two additional notations we need to explain before we continue to the posterior of $\mathbf{\Lambda}$. Let $\mathbf{F}_i$ be the matrix consisting of the first i columns of $\mathbf{F}$ for $i = 1, \ldots, r$ and $\mathbf{F}_i = \mathbf{F}$ for $i = r+1, \ldots, N$. Let $\mathbf{F}^* = diag(\mathbf{F}_1, \ldots, \mathbf{F}_N)'$. The conditional posterior of $\mathbf{\Lambda}$ is a multivariate normal distribution

$$\mathbf{\Lambda}/(\mathbf{W}, \mathbf{D}, \mathbf{F}) \backsim N(\overline{\boldsymbol{\lambda}}, \overline{\mathbf{H}}_{\Lambda}^{-1}) \tag{18}$$

where

$$\overline{\mathbf{H}}_{\Lambda} = \underline{\mathbf{H}}_{\Lambda} + \mathbf{F}^{*'}(\mathbf{D} \otimes \mathbf{I}_T)^{-1}\mathbf{F}^*$$
$$\overline{\boldsymbol{\lambda}} = \overline{\mathbf{H}}_{\Lambda}^{-1}[\underline{\mathbf{H}}_{\Lambda}.\underline{\boldsymbol{\lambda}} + \mathbf{F}^{*'}(\mathbf{D} \otimes \mathbf{I}_T)^{-1}\mathbf{W}]$$

with a truncation of the elements λ_{ii}'s, $i = 1 \ldots r$, below at 0.

Simulating the Latent Factors

We can rewrite the model and the factor dynamics in the following state space structure

$$\mathbf{w}_t = \mathbf{H}\mathbf{F}_t + \boldsymbol{\varepsilon}_t \tag{19}$$

where $\mathbf{H} = \begin{pmatrix} \lambda_{11} & \lambda_{22} & \lambda_{33} & \lambda_{44} & \lambda_{55} \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}'$ and $\mathbf{F}_t = \begin{pmatrix} f_t \\ e_t \end{pmatrix}$.

The evolution of the state vector is

$$\mathbf{F}_t = \mathbf{B}_0 + \mathbf{B}_1\mathbf{F}_{t-1} + \mathbf{E}_t \tag{20}$$

where $\mathbf{B}_0 = \begin{pmatrix} b_0 \\ 0 \end{pmatrix}$, $\mathbf{B} = \begin{pmatrix} b_1 & c_1 \\ 0 & 0 \end{pmatrix}$ and $\mathbf{E}_t = \begin{pmatrix} 1 \\ 1 \end{pmatrix} e_t$ Finally, the roots of $(1 - \sum_{s=1}^{p} b_s L^s) = 0$ lie outside the unit circle. Note that $Var(\mathbf{E}_t) = \sigma_t^2 \iota_4$ where ι_4 is a 4×4 matrix of ones.

Now we explain the simulation of latent factors (state variables in the model) with the use of Gibbs sampler. We employ Carter and Kohn (1994)'s Gibbs sampling approach for its computational efficiency and faster convergence. The step of the Gibbs sampler in which we generate $\mathbf{F}$ is given by:
$p(\mathbf{F}|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{F}})$
$= p(\mathbf{f}_T|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{F}}) \prod_{t=1}^{T-1} p(\mathbf{f}_t|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{F}}, \mathbf{f}_{t+1}, ..., \mathbf{f}_T)$
$= p(\mathbf{f}_T|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{F}}) \prod_{t=1}^{T-1} p(\mathbf{f}_t|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{F}}, \mathbf{f}_{t+1})$
The last line follows from the Markov property of $\mathbf{f}_t$.

Because the model is linear and Gaussian, the distribution of $\mathbf{f}_T$ given $\mathbf{W}$ and $\mathbf{\Theta}_{-\mathbf{F}}$, and that of $\mathbf{f}_t$ given $\mathbf{W}$, $\mathbf{\Theta}_{-\mathbf{F}}$ and $\mathbf{f}_{t+1}$ for $t = 1, ..., T$ are also Gaussian:

$$\mathbf{f}_T|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{F}} \sim N(\mathbf{f}_{T|T}, \mathbf{P}_{T|T}) \tag{21}$$

$$\mathbf{f}_t|\mathbf{W}, \mathbf{\Theta}_{-\mathbf{F}}, \mathbf{f}_{t+1} \sim N(\mathbf{f}_{t|t,\mathbf{f}_{t+1}}, \mathbf{P}_{t|t,\mathbf{f}_{t+1}}) \tag{22}$$

where

$$\mathbf{f}_{T|T} = E(\mathbf{f}_T|\mathbf{W})$$

$$\mathbf{P}_{T|T} = Cov(\mathbf{f}_T|\mathbf{W})$$

$$\mathbf{f}_{t|t,\mathbf{f}_{t+1}} = E(\mathbf{f}_T|\mathbf{W},\mathbf{f}_{t+1})$$

$$\mathbf{P}_{t|t,\mathbf{f}_{t+1}} = Cov(\mathbf{f}_T|\mathbf{W},\mathbf{f}_{t+1})$$

Computation of $\mathbf{f}_{T|T}$, $\mathbf{P}_{T|T}$, $\mathbf{f}_{t|t,\mathbf{f}_{t+1}}$ and $\mathbf{P}_{t|t,\mathbf{f}_{t+1}}$:

How can we compute these means and covariances, $\mathbf{f}_{T|T}$, $\mathbf{P}_{T|T}$, $\mathbf{f}_{t|t,\mathbf{f}_{t+1}}$ and $\mathbf{P}_{t|t,\mathbf{f}_{t+1}}$ for $t = T-1, T-2, ..., 1$? We can take the advantage of Gaussian Kalman filter to obtain $\mathbf{f}_{T|T}$, $\mathbf{P}_{T|T}$, $\mathbf{f}_{t|t,\mathbf{f}_{t+1}}$ and $\mathbf{P}_{t|t,\mathbf{f}_{t+1}}$ for $t = T-1, T-2, ..., 1$. Since the last iteration of the updating step of the Kalman filter procedure (which will be explained soon) provides us with $\mathbf{f}_{T|T}$ and $\mathbf{P}_{T|T}$, it is straightforward to generate $\mathbf{f}_T$ from (21). Then, as shown by Carter and Kohn (1994) and Kim and Nelson (2000), $\mathbf{f}_{t|t,\mathbf{f}_{t+1}}$ and $\mathbf{P}_{t|t,\mathbf{f}_{t+1}}$ can be computed by using the following updating equations:

$$\mathbf{f}_{t|t,\mathbf{f}_{t+1}} = \mathbf{f}_{t|t} + \mathbf{P}_{t|t}\mathbf{B}_1'(\mathbf{B}_1\mathbf{P}_{t|t}\mathbf{B}_1' + \sigma_t^2)^{-1}(\mathbf{f}_{t+1} - \mathbf{B}_0 - \mathbf{B}_1\mathbf{f}_{t|t}) \tag{23}$$

$$\mathbf{P}_{t|t,\mathbf{f}_{t+1}} = \mathbf{P}_{t|t} - \mathbf{P}_{t|t}\mathbf{B}_1'(\mathbf{B}_1\mathbf{P}_{t|t}\mathbf{B}_1' + \sigma_t^2)^{-1}\mathbf{B}_1\mathbf{P}_{t|t} \tag{24}$$

Once $\mathbf{f}_{t|t,\mathbf{f}_{t+1}}$ and $\mathbf{P}_{t|t,\mathbf{f}_{t+1}}$ are derived in this way, generating $\mathbf{f}_t$ from (22) is straightforward. However, we still do not know $\mathbf{f}_{t|t}$ and $\mathbf{P}_{t|t}$. We employ the Kalman filter procedure to derive $\mathbf{f}_{t|t}$ and $\mathbf{P}_{t|t}$ (see section 3.2 in Kim and Nelson (2000) for further discussions). Given the initial values $\mathbf{f}_{0|0}$ and $\mathbf{P}_{0|0}$, the following prediction and updating equations should be applied recursively to compute $\mathbf{f}_{t|t}$ and $\mathbf{P}_{t|t}$.
Prediction procedure of the Kalman filter:

$$\mathbf{f}_{t|t-1} = \mathbf{B}_0 + \mathbf{B}_1\mathbf{f}_{t-1|t-1}$$

$$\mathbf{P}_{t|t-1} = \mathbf{B}_1\mathbf{P}_{t-1|t-1}\mathbf{B}_1' + \sigma_t^2$$

$$\boldsymbol{\eta}_{\mathbf{t|t-1}} = \mathbf{w}_t - \mathbf{w}_{t|t-1} = \mathbf{w}_t - \mathbf{H}\mathbf{f}_{t|t-1}$$

$$\mathbf{g}_{t|t-1} = \mathbf{H}\mathbf{P}_{t-1|t-1}\mathbf{H}' + \mathbf{D}$$

Updating procedure of the Kalman filter:

$$\mathbf{f}_{t|t} = \mathbf{f}_{t|t-1} + \mathbf{K}_t\boldsymbol{\eta}_{\mathbf{t|t-1}}$$

$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{K}_t\mathbf{H}\mathbf{P}_{t|t-1}$$

where $\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{H}'\mathbf{g}_{t|t-1}^{-1}$ is the Kalman gain. However, there is one more complication of the estimation we need to solve. What initial values, $\mathbf{f}_{0|0}$ and $\mathbf{P}_{0|0}$, should we employ? Since $\mathbf{f}_t$ is stationary, we employ the unconditional mean and covariance matrix of $\mathbf{f}_t$ as the initial values, $\mathbf{f}_{0|0}$ and $\mathbf{P}_{0|0}$. The unconditional mean of stationary $\mathbf{f}_t$ can be derived as

$$E[\mathbf{f}_t] = \mathbf{B}_0 + \mathbf{B}_1E[\mathbf{f}_{t-1}] + E[\mathbf{e}_t]$$

$$\mathbf{f}_{0|0} = \mathbf{B}_0 + \mathbf{B}_1\mathbf{f}_{0|0} \quad (\textit{At Steady State})$$
$$\mathbf{f}_{0|0} = (\mathbf{I}_r - \mathbf{B}_1)^{-1}\mathbf{B}_0$$

The unconditional covariance matrix of stationary $\mathbf{f}_t$ can be derived as

$$Cov(\mathbf{f}_t) = \mathbf{B}_1 Cov(\mathbf{f}_{t-1})\mathbf{B}_1' + Cov(\mathbf{e}_t)$$
$$\mathbf{P}_{0|0} = \mathbf{B}_1\mathbf{P}_{0|0}\mathbf{B}_1' + \sigma_t^2 \quad (\textit{At Steady State})$$
$$vec(\mathbf{P}_{0|0}) = vec(\mathbf{B}_1\mathbf{P}_{0|0}\mathbf{B}_1') + vec(\sigma_t^2)$$
$$vec(\mathbf{P}_{0|0}) = (\mathbf{B}_1 \otimes \mathbf{B}_1)vec(\mathbf{P}_{0|0}) + vec(\sigma_t^2)$$
$$vec(\mathbf{P}_{0|0}) = (\mathbf{I}_{r^2} - \mathbf{B}_1 \otimes \mathbf{B}_1)^{-1}vec(\sigma_t^2)$$

since $vec(\mathbf{ABC}) = (\mathbf{C}' \otimes \mathbf{A})vec(\mathbf{B})$.

Figure 1: The Wave Measures Over Time

The figure shows the plots of the five corporate waves analyzed in this paper. The time series of each event wave is measured as the log of its aggregated dollar volume (in year 2000 dollars) per month. The considered five corporate events are Divestitures (DIV), Initial Public Offerings (IPO), Mergers&Acquisitions (MA), Equity Repurchases (REP), and Seasoned Equity Offerings (SEO). The time period is between 1981:01 and 2007:12.

Figure 1A: Monthly Observations of Divestitures Wave (Log Volume in year 2000 dollars)

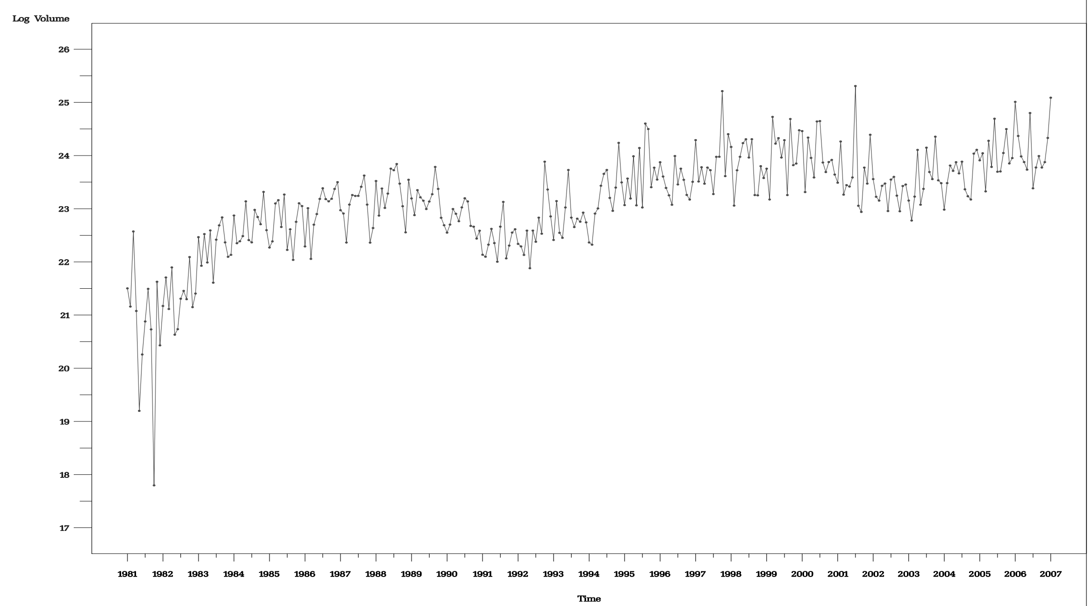


Figure 1B: Monthly Observations of IPOs Wave (Log Volume in year 2000 dollars)

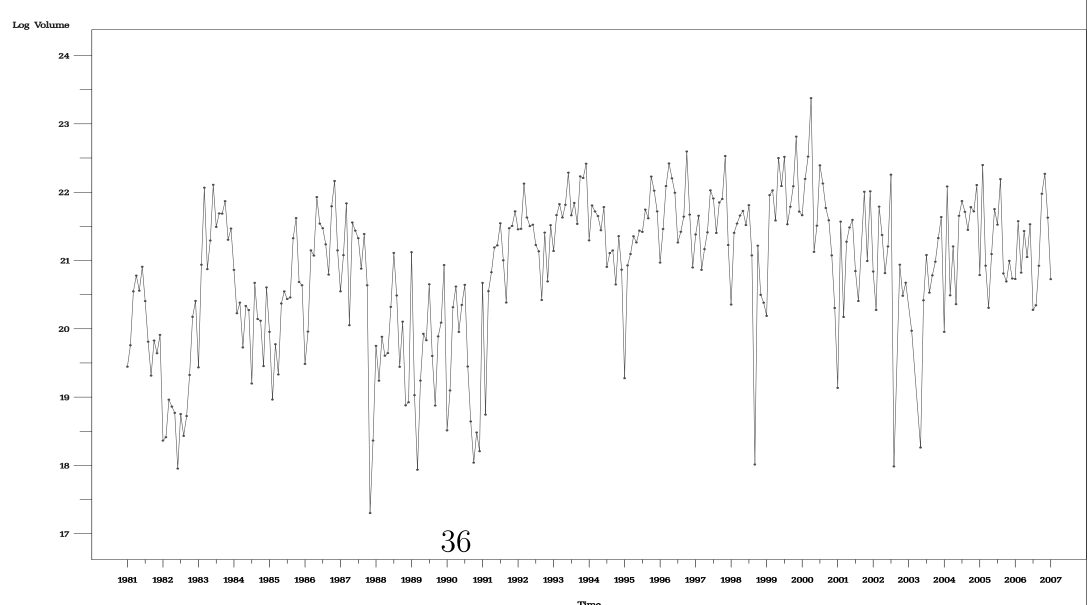


Figure 1C: Monthly Observations of M&As Wave (Log Volume in year 2000 dollars)

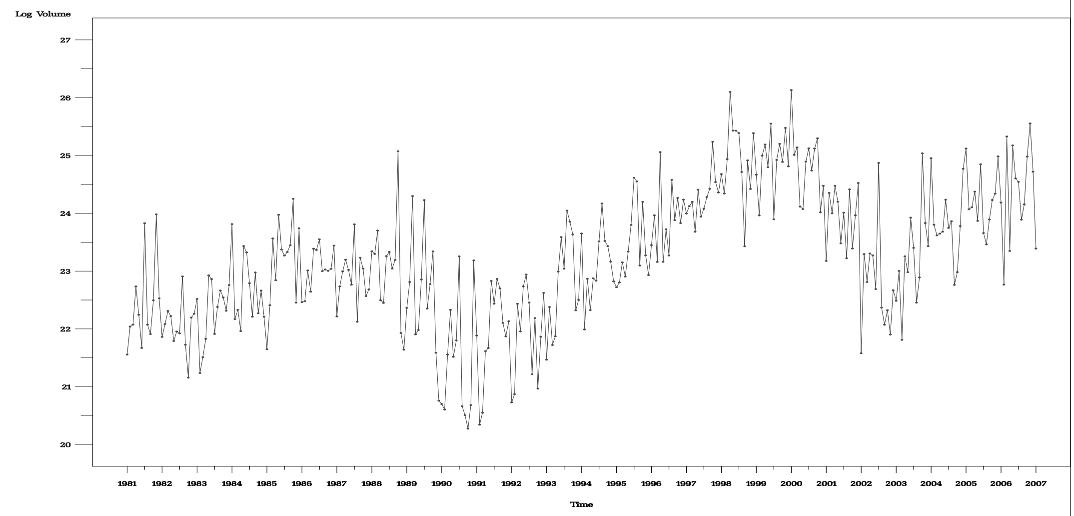


Figure 1D: Monthly Observations of Repurchases Wave (Log Volume in year 2000 dollars)

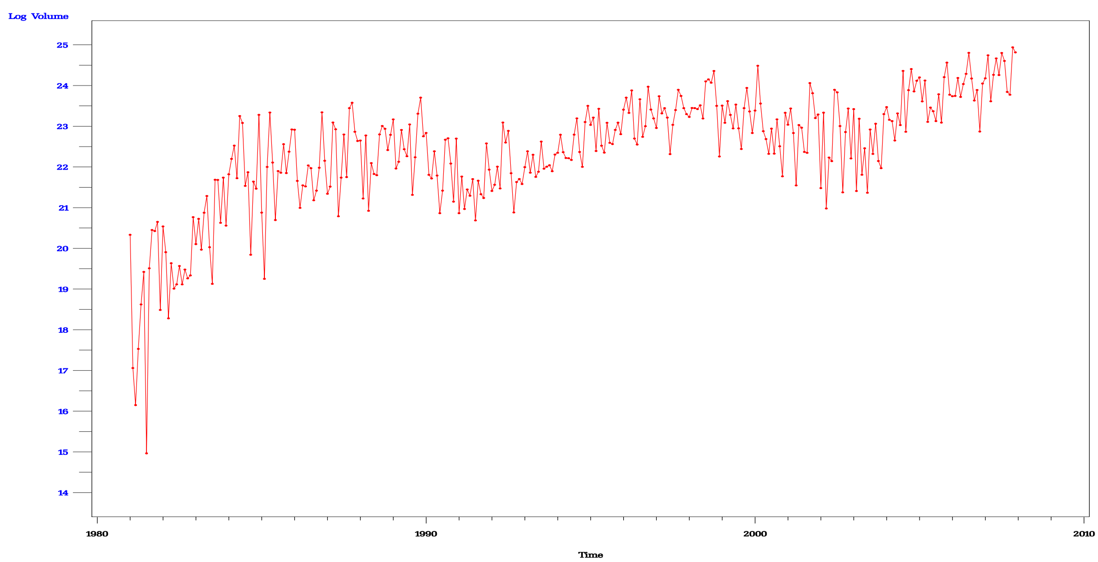


Figure 1E: Monthly Observations of SEOs Wave (Log Volume in year 2000 dollars)

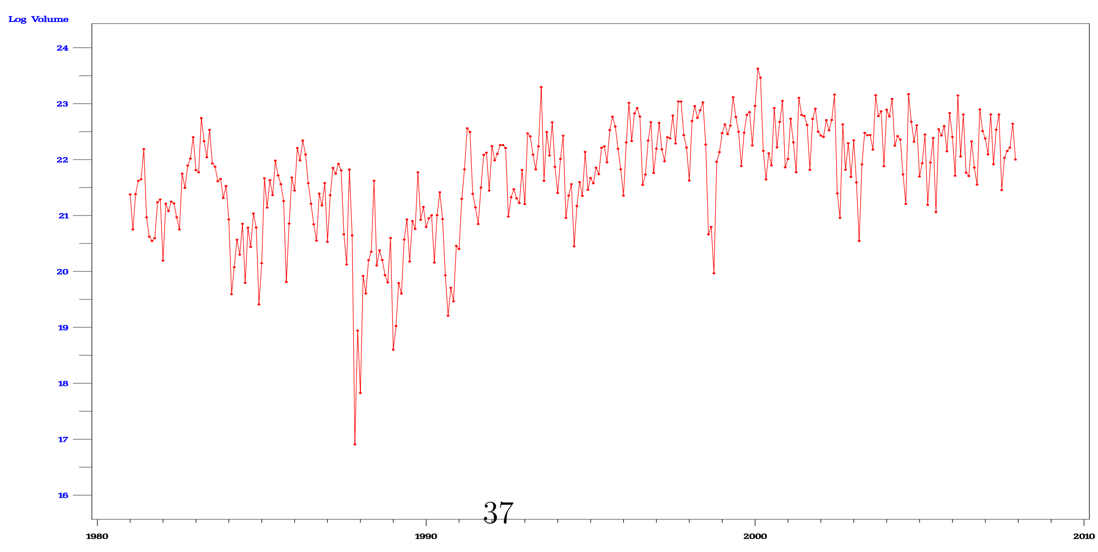
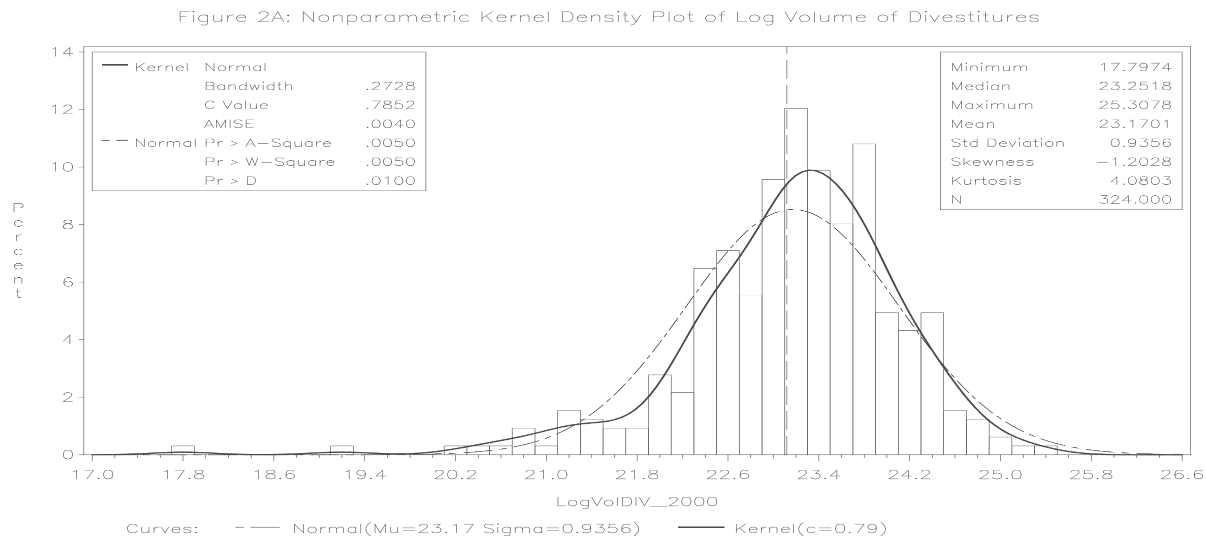


Figure 2: Descriptive Statistics of the Waves

The figure displays the nonparametric kernel density plots for the five event waves (DIV, IPO, MA, REP, and SEO waves). Type of kernel plot, bandwidth, c-value, and approximate mean integrated square error (AMISE) are shown in a little box on the graph. The same box also shows the results from three tests for normality of the distributions (the Anderson-Darling (*Pr > A-Square*), the Cramer-von Mises (*Pr > W-Square*), and the Kolmogorov-Smirnov (*Pr > D*)). The sample statistics, such as minimum, median, maximum, mean, variance, skewness, kurtosis, and number of firms for each heat sample are also displayed in a separate box. Dotted graph shows the fitted normal distribution with the same mean and variance as the actual distribution.



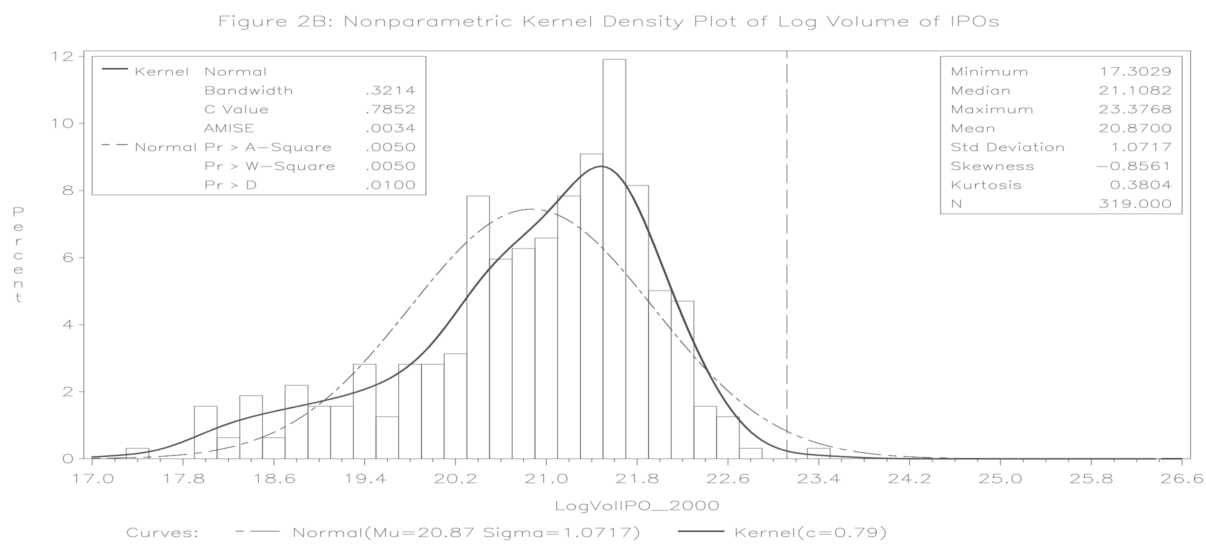


Figure 2C: Nonparametric Kernel Density Plot of Log Volume of M&As

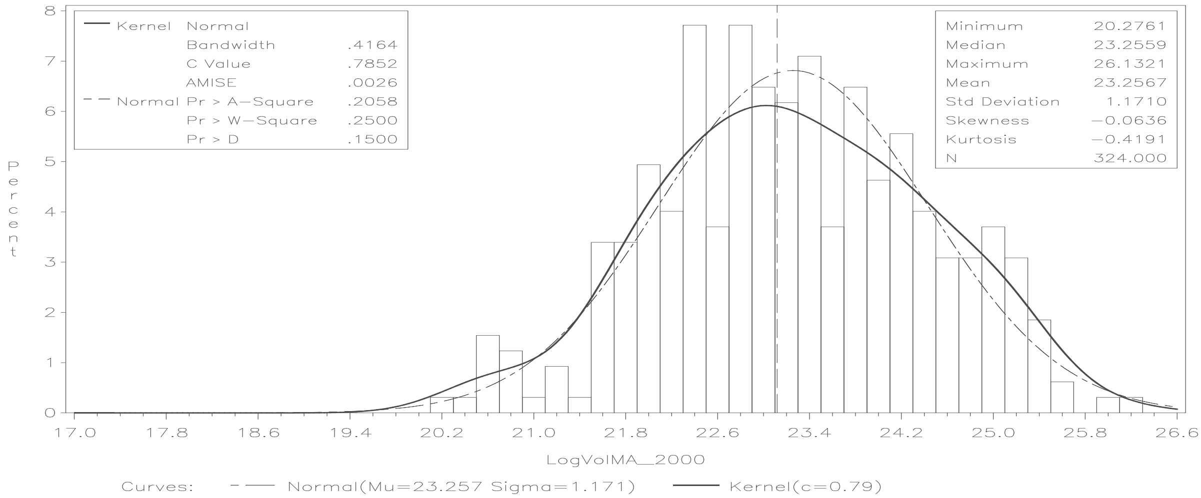


Figure 2D: Nonparametric Kernel Density Plot of Log Volume of Repurchases

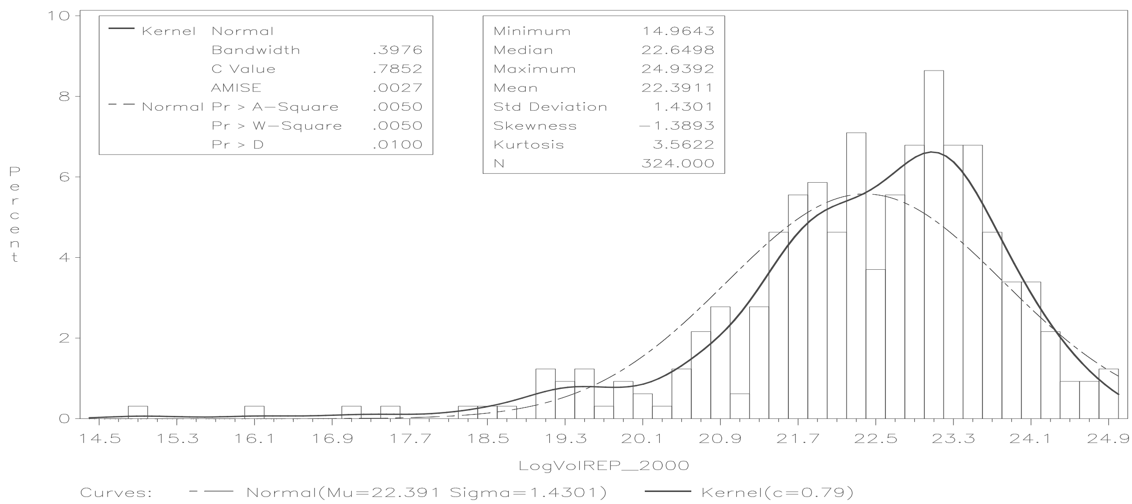


Figure 2E: Nonparametric Kernel Density Plot of Log Volume of SEOs

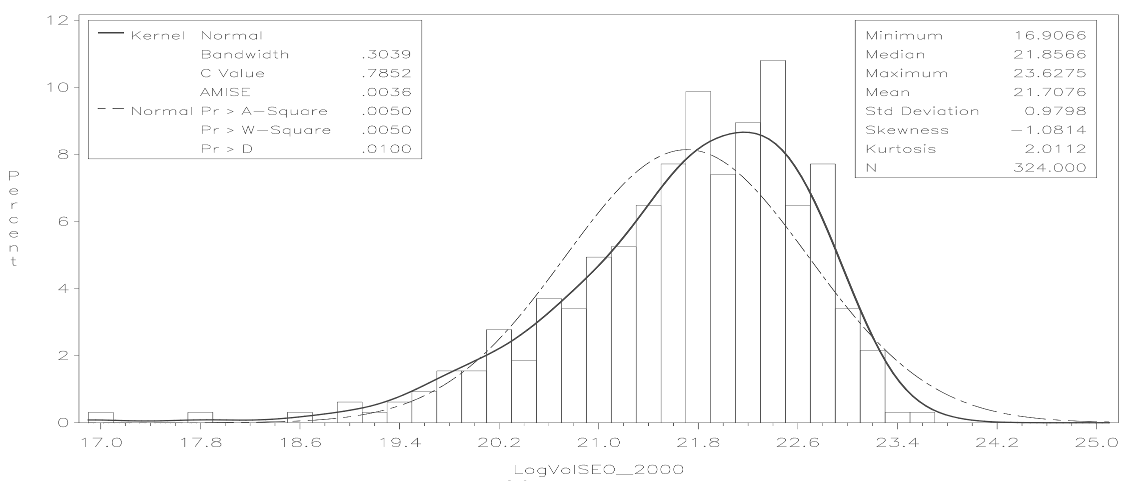


Figure 3: Correlation Coefficients Over Time

Figures 3A-L show the time variation in the correlation coefficients over time for each pair of waves. The correlation coefficients are estimated using a 36-month moving window of the monthly data observations of our event time-series (the window shifts one month at a time). The analyzed waves are DIV, IPO, MA, REP, and SEO waves, and are calculated as described earlier. The time period is between 1981:01 and 2007:12.

Figure 3A: Change in Correlation of DIV and IPO Waves Over Time (rolling window=36 mos.)

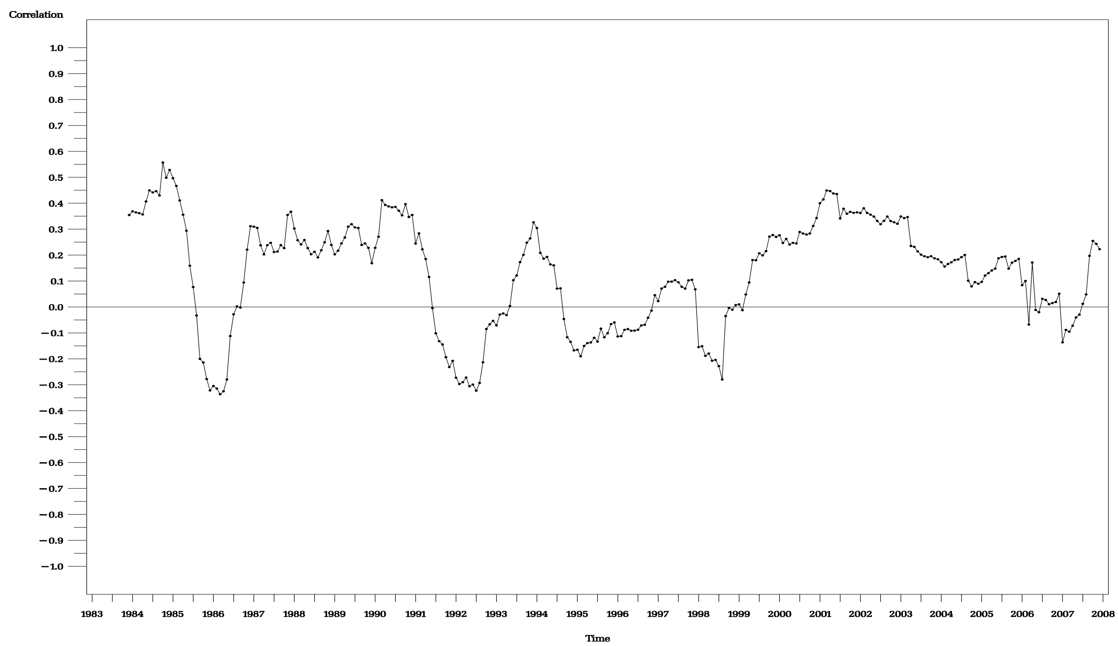


Figure 3B: Change in Correlation of DIV and M&A Waves Over Time (rolling window=36 mos.)

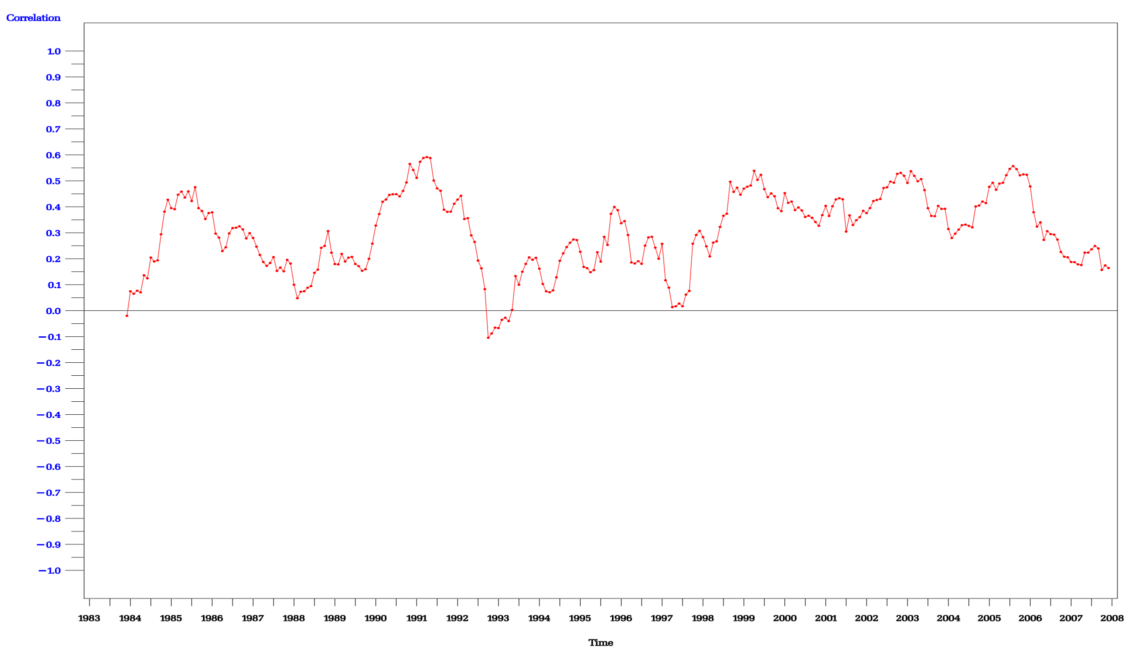


Figure 3C: Change in Correlation of DIV and SEO Waves Over Time (rolling window=36 mos.)

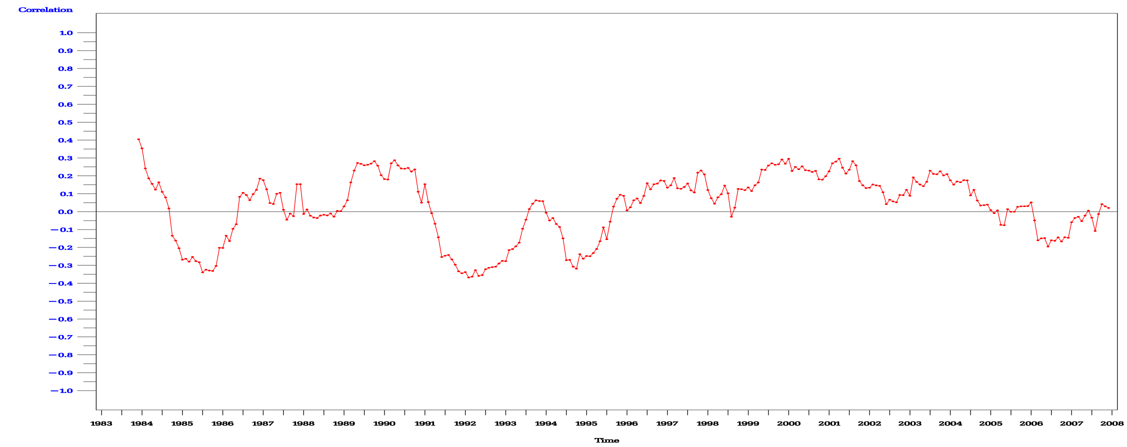


Figure 3D: Change in Correlation of IPO and M&A Waves Over Time (rolling window=36 mos.)

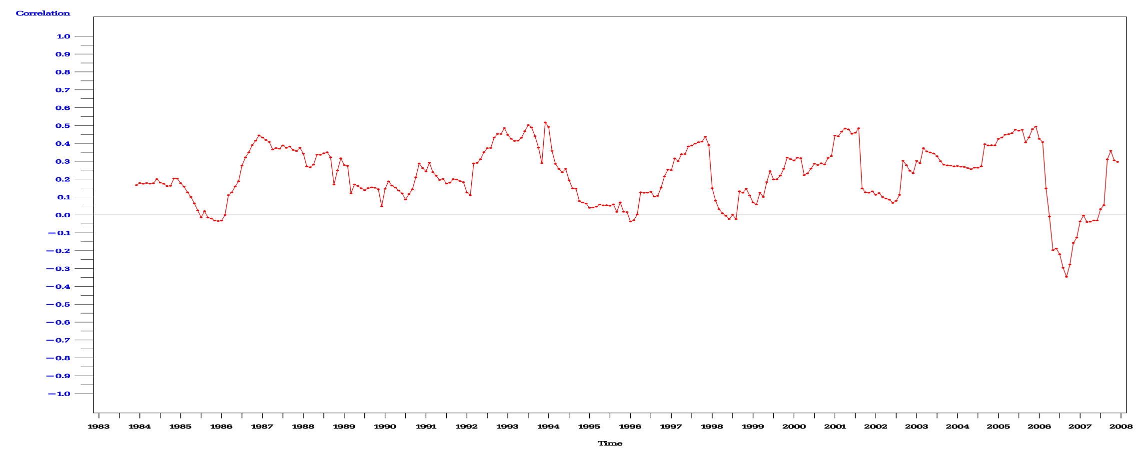


Figure 3E: Change in Correlation of IPO and SEO Waves Over Time (rolling window=36 mos.)

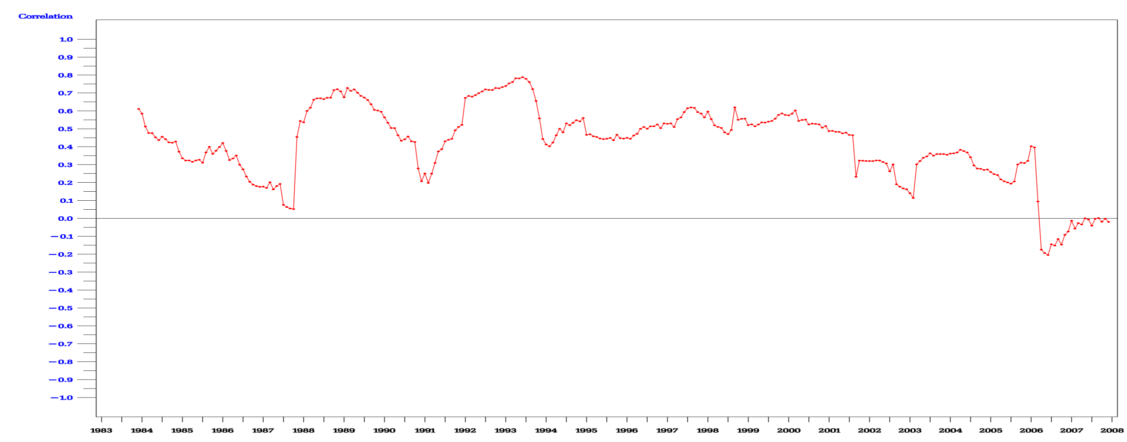


Figure 3F: Change in Correlation of M&A and SEO Waves Over Time (rolling window=36 mos.)

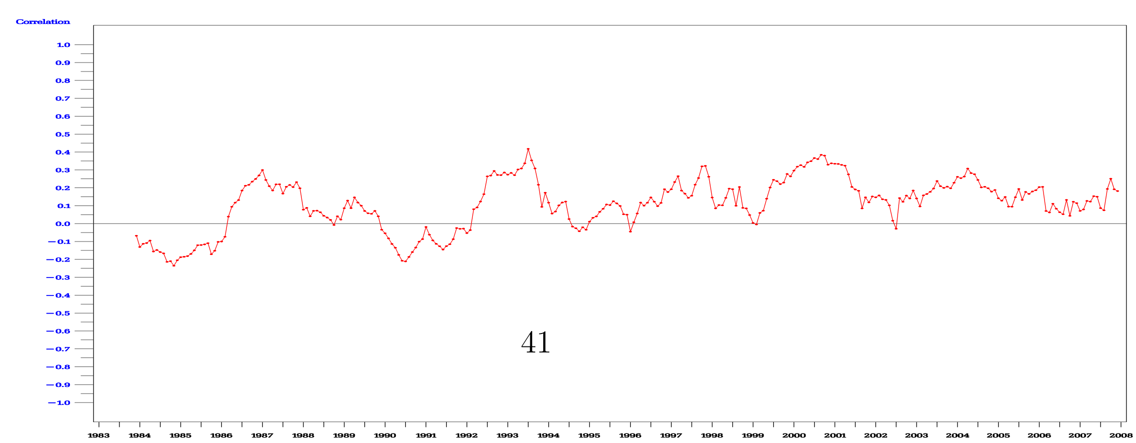


Figure 3G: Change in Correlation of DIV and REP Waves Over Time (rolling window=36 mos.)

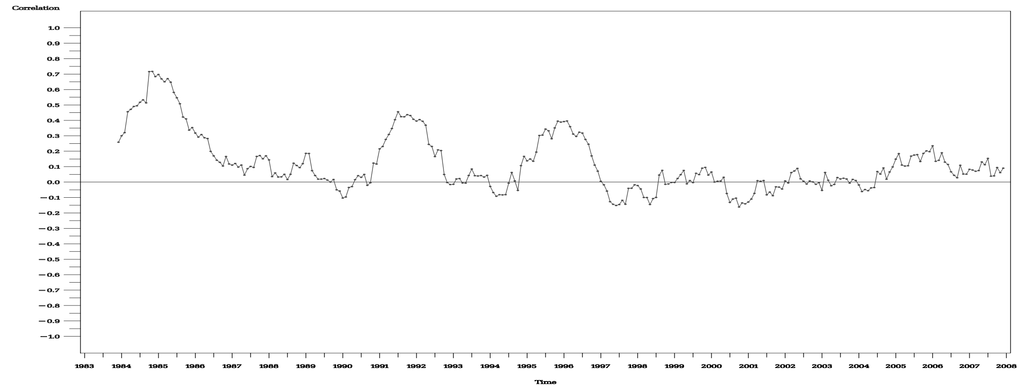


Figure 3H: Change in Correlation of IPO and REP Waves Over Time (rolling window=36 mos.)

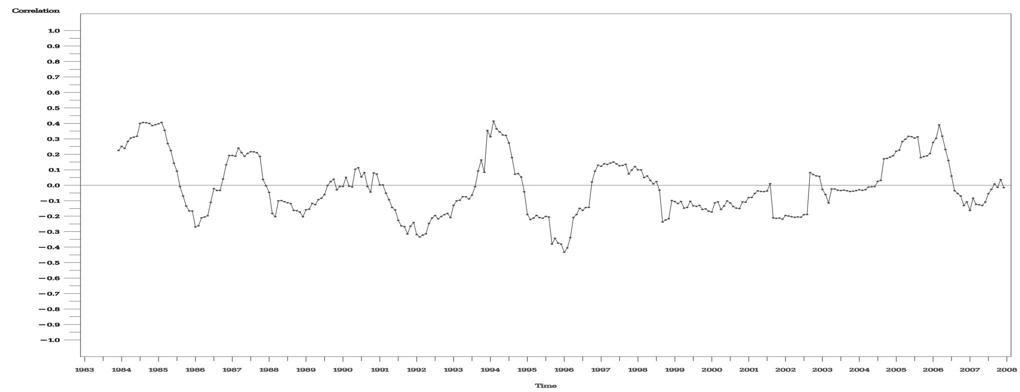


Figure 3K: Change in Correlation of M&A and REP Waves Over Time (rolling window=36 mos.)

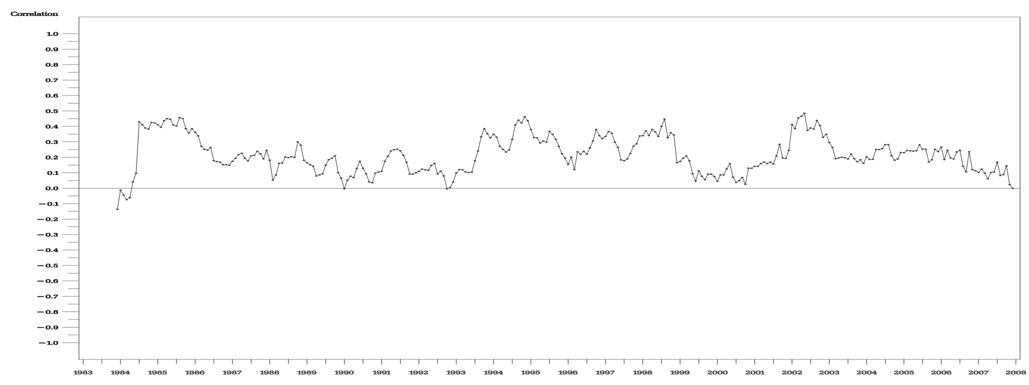


Figure 3L: Change in Correlation of SEO and REP Waves Over Time (rolling window=36 mos.)

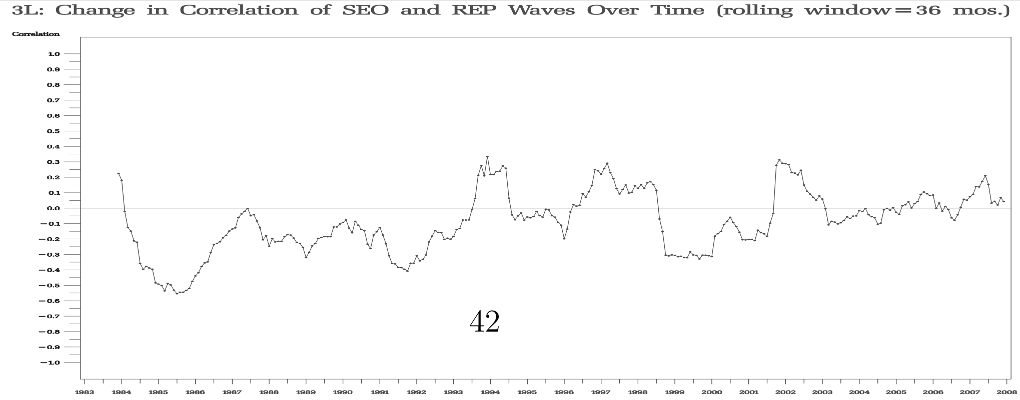


Figure 4: The Common Factor Over Time

This figure plots the estimated common factor of the waves between 1981:01 and 2007:12. The time series of the corporate events are measured in aggregated dollar volume (in year 2000 dollars) per month. The considered five corporate event series are Divestitures (DIV), Initial Public Offerings (IPO), Mergers&Acquisitions (MA), Equity Repurchases (REP), and Seasoned Equity Offerings (SEO). The factor is extracted using the Bayesian methodology we develop and describe in the text.

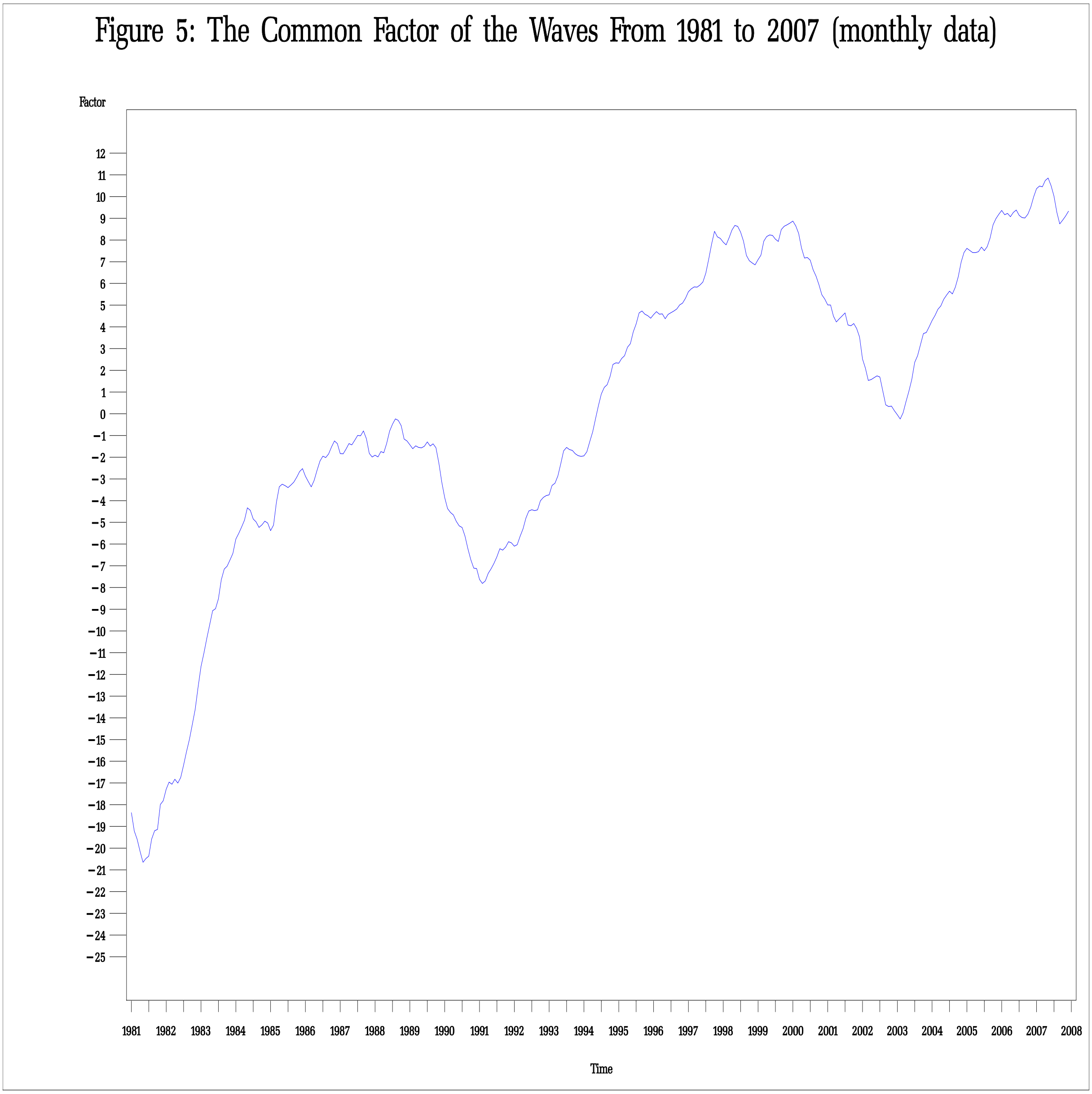


Table 2: Fitting an $ARMA(p, q)$ Model to the Wave Series

This table presents the results from estimating autoregressive moving average (ARMA) models for DIV, IPO, M&A, REP, and SEO waves. The wave variables measured as natural logarithm of volume levels (in year 2000 dollars) are LogVolDIV, LogVolIPO, LogVolMA, LogVolREP, and LogVolSEO. The estimated ARMA(1,1) model is of the form $w_t = \psi_0 + \theta_1 w_{t-1} + \epsilon_t + \gamma_1 \epsilon_{t-1}$. The number in parantheses under the coefficient estimate represent the p-value of the null hypothesis of zero coefficient estimate. MINIC is the Minimum Bayesian Information Criterion used in selecting the appropriate ARMA model. AIC and SBC are Akaike Information Criterion and Schwarz Bayesian Criterion, respectively.

	LogVolDIV	LogVolIPO	LogVolMA	LogVolREP	LogVolSEO
ψ_0	22.4397	20.7618	22.8744	19.1527	21.6750
(p-value)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
θ_1	0.9817	0.9156	0.9871	0.9997	0.8978
(p-value)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
γ_1	0.7117	0.5480	0.7392	0.7317	0.4037
(p-value)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AIC	518.1445	765.9897	738.7720	777.0423	648.5087
SBC	529.4868	777.2853	750.1142	788.3845	659.8509
MINIC	-1.5229	-0.4368	-0.5599	-0.6112	-0.8508
Monthly Obs.	324	319	324	324	324

Table 3: Fitting a $GARCH(p, q)$ Model to the Wave Series

This table presents the results from estimating autoregressive conditional heteroscedasticity ($GARCH(1, 1)$) model for DIV, IPO, M&A, REP, and SEO waves. The wave variables measured as natural logarithm of volume levels (in year 2000 dollars) are LogVolDIV, LogVolIPO, LogVolMA, LogVolREP, and LogVolSEO. The formal description of the estimated $GARCH(1, 1)$ equations is presented in the text. The number in parantheses under the coefficient estimate represent the p-value of the null hypothesis of zero coefficient estimate. AIC, SBC, and LogL are Akaike Information Criterion, Schwarz Bayesian Criterion, and Log Likelihood Function, respectively. The parameters are estimated assuming t-distribution for the residuals.

	LogVolDIV	LogVolIPO	LogVolMA	LogVolREP	LogVolSEO
Intercept	23.3228	21.2678	23.1997	22.6452	22.0903
(p-value)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ARCH0	0.0368	0.2594	0.0630	0.0493	0.1846
(p-value)	(0.0967)	(0.0025)	(0.1356)	(0.1448)	(0.0002)
ARCH1	0.2030	0.6456	0.1813	0.2248	0.6553
(p-value)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)
GARCH1	0.7418	0.2777	0.7700	0.7488	0.2053
(p-value)	(0.0001)	(0.0247)	(0.0001)	(0.0001)	(0.0471)
LogL	-176.9007	-261.0358	-294.7743	-297.8122	-214.0594
AIC	361.8014	532.0717	597.5486	603.6245	436.1188
SBC	376.9243	550.8976	612.6715	618.7474	451.2418

Table 4: Granger Causality Tests

Granger causality estimation and test results are presented in this table. The waves are measured as natural logarithm of the corresponding volume levels (in year 2000 dollars): LogVolDIV, LogVolIPO, LogVolMA, LogVolREP, and LogVolSEO. The estimated equations are Eqn 1: $w_{i,t} = \pi_0 + \pi_1 w_{i,t-1} + \pi_2 w_{j,t-1} + \pi_3 w_{i,t-2} + \pi_4 w_{j,t-2} + \xi_{i,t}$ and Eqn 2: $w_{j,t} = \eta_0 + \eta_1 w_{j,t-1} + \eta_2 w_{i,t-1} + \eta_3 w_{j,t-2} + \eta_4 w_{i,t-2} + \xi_{j,t}$. The waves are grouped in pairs (w_i,w_j). The first equation is used to test for wave w_j Granger causing wave w_i and second equation is used to test for the reverse causation. The null hypothesis of no Granger causality for Eqn. 1 is $H_0 : \pi_2 = 0,\ \pi_4 = 0$; and for Eqn. 2 is $H_0 : \eta_2 = 0,\ \eta_4 = 0$. The numbers in parantheses under the the coefficient estimates are the corresponding p-values. Wald test results from a VAR estimation is also reported as official test of the null of wave w_j not Granger causing wave w_i. "*" indicates significance at 5% level.

	w_i=DIV w_j=IPO	w_i=DIV w_j=MA	w_i=DIV w_j=SEO	w_i=IPO w_j=MA	w_i=IPO w_j=SEO	w_i=MA w_j=SEO	w_i=DIV w_j=REP	w_i=IPO w_j=REP	w_i=MA w_j=REP	w_i=SEO w_j=REP
π_2	0.0020	0.0749	0.0540	0.4730	0.8375	0.2453	0.0503	0.2388	0.0747	-0.0102
(p-value)	(0.8710)	(0.0415)*	(0.2545)	(0.0069)*	(0.0001)*	(0.0002)*	(0.1750)	(0.1395)	(0.1364)	(0.8053)
η_2	0.4687	0.0467	0.0246	-0.0001	0.0106	0.0128	0.1770	-0.1579	0.0324	0.0382
(p-value)	(0.0509)	(0.5397)	(0.6872)	(0.9990)	(0.4555)	(0.7787)	(0.0001)*	(0.3280)	(0.5164)	(0.3500)
π_4	0.0068	0.0537	0.0313	0.2459	-0.4311	-0.0902	0.2561	0.0223	0.0708	0.0844
(p-value)	(0.5730)	(0.1845)	(0.5114)	(0.1589)	(0.0457)*	(0.1735)	(0.0009)*	(0.2124)	(0.2177)	(0.2227)
η_4	-0.3232	0.1675	0.0401	0.0139	-0.0066	0.0613	0.4165	-0.0008	0.1159	0.0707
(p-value)	(0.1742)	(0.0261)*	(0.5084)	(0.4453)	(0.6387)	(0.1690)	(0.0001)*	(0.9650)	(0.0560)	(0.3121)
Wald Test (p-values):										
Eqn. 1:	(0.8042)	(0.0043)*	(0.0764)	(0.0208)*	(0.0002)*	(0.0003)*	(0.0001)*	(0.3244)	(0.2890)	(0.5096)
Eqn. 2:	(0.1423)	(0.0040)*	(0.3670)	(0.7298)	(0.5938)	(0.1351)	(0.0001)*	(0.4317)	(0.0020)*	(0.1540)