

# Time-series and cross-sectional excess comovement in stock indexes<sup>☆</sup>

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## Abstract

This paper is an empirical investigation of the excess comovement among 82 industry indexes in the U.S. stock market between January 5, 1976 and December 31, 2001. We define excess comovement as the covariation between two assets beyond what can be explained by fundamental factors. In our analysis, the fundamental factors are sector groupings and the three Fama-French factors. We then estimate residuals of joint (FGLS) rolling regressions of these fundamentals on industry returns. Finally, we compute excess comovement as the mean of square unconditional, statistically significant correlations of these residuals. We show that excess comovement is high (about 0.07, i.e., equivalent to an average absolute correlation of 0.26), statistically significant, and represents an economically significant portion (almost 30%) of the average gross square return correlation. Excess comovement is also uniformly significant across industries and over time and only weakly asymmetric, i.e., not significantly different in rising or falling markets.

We explain more than 23% of this market-wide (and up to 73% of sector-wide) excess square correlation by its positive relation to proxies for information heterogeneity and U.S. monetary and real conditions, and its negative relation to market volatility and the level of the short-term interest rate. This evidence is consistent with the implications of portfolio rebalancing and product market theories of financial contagion, but offers little or no support for the correlated liquidity shock channel.

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## 1. Introduction

The study of the correlations between different classes of securities is crucial to asset pricing. The recent economic literature has examined the issue of whether or not the observed degree of comovement is “excessive.” While the roots of this debate trace back to the early research in portfolio theory, precise notions of excess comovement are more

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recent. This debate has been especially relevant in the extensive literature dealing with financial crises and the propagation of shocks within and across markets.<sup>1</sup> Many of these papers use observed increases in correlation as a measure of financial contagion, and analyze whether those increases are due to the irrational propagation of shocks or merely to the surge in the variance of a common source of risk driving returns in the affected markets. This approach, however, does not easily reconcile with the definition of financial contagion as a pervasive feature of capital markets during both tranquil and uncertain times. Indeed, the prevailing view among researchers is that comovement among asset prices is excessive just when beyond the degree justified by economic fundamentals, i.e., by factors affecting assets' payoffs at liquidation.

In response to the evidence stemming from this growing body of empirical studies, the theoretical analysis of financial contagion has also gained momentum. Excess comovement has alternatively been interpreted as due to pure information transmission (King and Wadhwani, 1990), wealth effects (Kyle and Xiong, 2001), financial constraints (Calvo, 1999; Yuan, 2005), sunspot equilibria (Masson, 1998), the fragility of financial markets (Allen and Gale, 2000), the rebalancing activity of risk-averse agents (Fleming et al., 1998; Kodres and Pritsker, 2002), strategic trading by heterogeneously informed speculators (Pasquariello, 2007), relative real output shocks (Pavlova and Rigobon, 2007), the cost of acquiring information (Veldkamp, 2006), or investors' trading patterns (Barberis et al., 2005). Nevertheless, in spite of this abundance of explanations, no "horse race" among these competing (albeit seldom mutually exclusive) theories has yet emerged to ascertain their relevance in the data.

In this paper we empirically address both these issues by analyzing the time series of index returns of all major industry groups in the U.S. stock market for which data are available between 1976 and 2001 (82 in total). We utilize the factor portfolios suggested by Fama and French (1993) and a set of sector groupings to account for the correlation between these indexes due to observed "common factors," i.e., to existing *interdependence*. We then use the term *contagion* to refer to covariation above this level. More specifically, we define excess correlation as the *square* unconditional, statistically significant correlation of the estimated residuals from joint regressions of industry returns on these observed common factors. This definition is motivated by the necessity not to confine the concept of contagion to specific directional movements and by the availability of several tests in the literature for the statistical significance of the coefficient of determination. The industry correlations are adjusted for short-term volatility shifts and estimated on a rolling biannual basis to mitigate problems with the non-stationarity of stock returns over our long sample period. Finally, we explore the relation between the level of excess square correlation and market (and sector) returns and return volatility, the dispersion of analysts' earnings forecasts, market momentum, market (and sector) trends, fluctuations in interest rates, the state of the U.S. economy, and seasonality effects.

Briefly stated, our key findings are as follows. Our fundamental regression model, albeit quite successful, cannot fully explain return comovement in the U.S. equity market. Indeed, the average excess comovement across the entire sample, measured by the square unconditional correlation of regression residuals, is high (0.065, i.e., equivalent to an average absolute correlation of 0.255), statistically significant, and represents an economically significant portion (about 27%) of the benchmark square correlation estimated from the raw return series. Furthermore, this excess comovement is highly pervasive: Excess square correlations are significantly different from zero for each of our industry groups and for between 14% and 23% of all residual correlations at any given time. These measures are also robust to several alternative estimation methodologies, generally symmetric (i.e., associated with both bull and bear markets), and do not display any significant relation with levels of market returns or proxies for market momentum.

Excess comovement is, however, positively related to information heterogeneity and U.S. monetary and real output developments, and negatively related to long-term market volatility and the level of the short-term interest rate. This evidence offers little or no support for liquidity-based theories of financial contagion (the "correlated liquidity shock channel" of Calvo, 1999; Kyle and Xiong, 2001; Yuan, 2005), but is consistent with models interpreting excess comovement as a symmetric phenomenon due to the portfolio rebalancing activity of investors (e.g., Kodres and Pritsker, 2002; Pasquariello, 2007) or to product market shocks (Pavlova and Rigobon, 2007).

Our work is closest in spirit to Pindyck and Rotemberg (1990, 1993). Pindyck and Rotemberg (1990) find evidence of excess comovement among seven "largely unrelated" commodities (even after correcting for forecasts of aggregate

<sup>1</sup> A partial list of recent contributions includes Shiller (1989), King and Wadhwani (1990), Pindyck and Rotemberg (1990, 1993), King et al. (1994), Karolyi and Stulz (1996), Baig and Goldfajn (1999), Bekaert and Harvey (2000), Connolly and Wang (2000), Forbes and Rigobon (2001, 2002), Bae et al. (2003), Barberis et al. (2005), Bekaert et al. (2005), Corsetti et al. (2005), Kallberg et al. (2005), and Boyer et al. (2006).

production and inflation) and attribute it to investors in multi-commodity portfolios facing liquidity constraints.<sup>2</sup> Yet, Deb et al. (1996) show that the extent of such excess comovement significantly declines when accounting for heteroskedasticity and non-normality of commodity prices. Pindyck and Rotemberg (1993) test for excess comovement among only a subset of industry groups in the U.S. selected according to whether they operate in different business lines and their earnings are uncorrelated. Building on the factor analysis of Meyers (1973), they then regress those industries' returns on observed and latent macroeconomic factors and estimate the correlations of the resulting residuals. As in their previous study, Pindyck and Rotemberg (1993) find evidence of excess correlation, but relate it to patterns in the holdings of stocks by institutions.

The remainder of the paper is organized in the following way. Section 2 develops our econometric approach to estimating excess comovement. Section 3 describes the dataset employed in the analysis. Section 4 summarizes our estimation results. Section 5 tests for the significance of many of the proposed explanations for excess comovement mentioned above. Section 6 contains our conclusions.

## 2. Measuring excess covariance

### 2.1. The basic estimation strategy

An intense debate in the literature centers on the problem of identifying and measuring international financial contagion. Nonetheless, a consensus has appeared among researchers that not only periods of uncertainty but also more tranquil times may be accompanied by excess comovement among asset prices within and across both developed and emerging financial markets.<sup>3</sup> As in Pasquariello (2007), we define such *excess comovement* as comovement beyond the degree that is justified by economic fundamentals — i.e., by factors affecting payoffs at liquidation — and *financial contagion* as the circumstance of its occurrence.

In this section we propose a simple measure of the degree of intertemporal excess comovement among a set of  $K$  asset prices. The starting point of the analysis is the specification of a multi-factor model of each asset's return with time-varying sensitivities. Let  $r_{kt}$  be an  $N \times 1$  vector of returns for asset  $k$  over the interval  $[t-N+1, t]$ . We assume that, for each asset  $k=1, \dots, K$ , the return  $r_{kt}$  is characterized by the following linear factor structure:

$$r_{kt} = \alpha_{kt} + u_{bt}\beta_{kt} + f_t\gamma_{kt} + e_{kt}, \quad (1)$$

where  $u_{bt}$  is a  $N \times N_u$  matrix of observed systematic sources of risk affecting specific subsets, or blocks of assets (i.e.,  $k \in b$ ),  $f_t$  is an  $N \times N_f$  matrix of observed systematic shocks affecting all assets, and  $\beta_{kt}$  and  $\gamma_{kt}$  are ( $N_u \times 1$  and  $N_f \times 1$ , respectively) vectors of factor loadings. In this setting, comovement between any pairs of returns  $r_{kt}$  and  $r_{nt}$  is deemed excessive if, even after controlling for  $u$  and  $f$ , those returns are still correlated.

Measurement of such degree of comovement, if any, at each point in time  $t$  requires first the estimation of the parameters in Eq. (1), using sample data for the period  $[0, T]$  and a chosen set of block-common and systematic factors. The resulting estimated residuals  $\hat{e}_{kt}$ , where

$$\hat{e}_{kt} = r_{kt} - \hat{\alpha}_{kt} - u_{bt}\hat{\beta}_{kt} - f_t\hat{\gamma}_{kt}, \quad (2)$$

are then used to compute, for each  $k \neq n$ , excess correlation coefficients

$$\hat{\rho}_{knt} = \frac{\text{cov}(\hat{e}_{kt}, \hat{e}_{nt})}{[\text{var}(\hat{e}_{kt})\text{var}(\hat{e}_{nt})]^{1/2}}. \quad (3)$$

Boyer et al. (1999), Loretan and English (2000), and Forbes and Rigobon (2002) show that correlation coefficients like those in Eq. (3) are conditional on asset volatility; hence, in the presence of heteroskedasticity, tests for contagion based on such coefficients may be biased toward rejection of the null hypothesis of no excess comovement among asset

<sup>2</sup> Pindyck and Rotemberg (1990) define commodities as fundamentally unrelated when they are not substitutes nor complements of each other, they are not grown in similar climates, and their cross-price elasticities of demand and supply are insignificant.

<sup>3</sup> See, for example, the empirical studies by Pindyck and Rotemberg (1990, 1993), Karolyi and Stulz (1996), Fleming et al. (1998), and Barberis et al. (2005). Many theoretical models (e.g., King and Wadhwani, 1990; Kodres and Pritsker, 2002; Veldkamp, 2006; Pasquariello, 2007) also describe contagion as a pervasive equilibrium property of a financial market.

returns. The bias can however be corrected, these authors argued, and an unconditional correlation measure can be computed for any pair of return variables under the assumption of no omitted variables or endogeneity. The measure of excess comovement between  $r_{kt}$  and  $r_{nt}$  that we adopt in this paper is based on their proposed adjustment and is given by

$$\hat{\rho}_{knt}^* = \frac{\hat{\rho}_{knt}}{\left\{1 + \hat{\delta}_{kt}[1 - (\hat{\rho}_{knt})^2]\right\}^{\frac{1}{2}}}, \quad (4)$$

where the ratio  $\hat{\delta}_{kt} = \frac{\text{var}(\hat{e}_{kt})}{\text{var}(\hat{e}_{kt})_{LT}} - 1$ , when different from zero, corrects the short-term, conditional correlation  $\hat{\rho}_{knt}$  for the relative difference between short-term volatility ( $\text{var}(\hat{e}_{kt})$ ) and long-term volatility ( $\text{var}(\hat{e}_{kt})_{LT}$ ) of  $r_{kt}$ . Because we do not make any ex ante conjecture on the direction of propagation of shocks from one asset to another, we alternatively assume that the source of these shocks is asset  $k$  (in  $\hat{\rho}_{knt}^*$ ) or asset  $n$  (in  $\hat{\rho}_{nkt}^*$ ). This implies that  $\hat{\rho}_{knt}^*$  may be different from  $\hat{\rho}_{nkt}^*$ .

We then compute arithmetic means of pairwise adjusted correlation coefficients for each asset  $k$ , along the lines of King et al. (1994). Much of the literature on financial contagion explores the circumstances in which correlation among asset prices becomes more positive (or less negative) during crisis periods. However, as is clear from Eq. (1), there is no reason to restrict the concept of excess comovement to a specific directional move in the correlation coefficients. In other words, both  $\hat{\rho}_{knt}^* \neq 0$  and  $\hat{\rho}_{nkt}^* \neq 0$  represent evidence of comovement between assets  $k$  and  $n$  beyond what is implied by their fundamentals, regardless of their sign. Thus, we need a contagion measure that prevents such coefficients, if of different sign, from cancelling each other out in the aggregation. This measure needs to control for sample variation as well. Because of sample variation in the estimators  $\hat{\alpha}_{kt}$  and  $\hat{\alpha}_{nt}$ ,  $\hat{\beta}_{kt}$  and  $\hat{\beta}_{nt}$ , and  $\hat{\gamma}_{kt}$  and  $\hat{\gamma}_{nt}$ , residuals' correlations  $\hat{\rho}_{knt}$  are estimated with error over  $N$  observations; hence, failure to account for statistically insignificant  $\hat{\rho}_{knt}$  may bias our analysis of the significance and extent of excess return comovement. Consequently, we focus only on statistically significant conditional correlations, according to the  $t$ -ratio test  $\hat{t}_{knt} = \hat{\rho}_{knt} \left[ \frac{1 - (\hat{\rho}_{knt})^2}{N-2} \right]^{-\frac{1}{2}} \sim t[N-2]$ , and measure excess comovement by computing the following means of excess square correlations:

$$\hat{\rho}_{kt}^* = \frac{1}{N_{kt}} \sum_{n \neq k}^K (\hat{\rho}_{knt}^*)^2 I_{knt}, \quad (5)$$

where  $I_{knt} = 1$  if  $2 \left[ 1 - \Pr\left\{|\hat{t}_{knt}| \leq t_{\frac{\alpha}{2}}[N-2]\right\} \right] \leq \alpha$  and  $I_{knt} = 0$  otherwise and  $N_{kt} = \sum_{n \neq k}^K I_{knt}$ , for any  $k = 1, \dots, K$ . Eq. (5) implies that there is statistically significant excess comovement for asset  $k$  at time  $t$  if  $\hat{\rho}_{kt}^*$  is different from zero.<sup>4</sup> We also compute a market-wide measure of financial contagion as a mean of means of excess square correlation coefficients across all the traded assets, i.e.,

$$\hat{\rho}_t^* = \frac{1}{K} \sum_{k=1}^K \hat{\rho}_{kt}^*. \quad (6)$$

Finally, we want to evaluate the evolution of such measures over time while accounting for the dynamics of the fundamental interdependence among asset returns and of their variances. Ignoring time-varying factor loadings and non-stationary variances in Eq. (1) may in fact bias the inference on non-fundamental comovement from Eqs. (5) and (6). Parametric ARCH and stochastic volatility models, as well as their generalizations to multivariate settings, are frequently employed to describe such dynamics.<sup>5</sup> Nonetheless, these models are in general very difficult to estimate and do not offer a clear advantage over simpler, nonparametric approaches, especially when used to measure covariance, rather than forecast it. Indeed, Campbell et al. (1997) observe that rolling filters — like the rolling standard deviation measure used by Officer (1973) — usually provide very accurate descriptions of historical variation (or comovement), in particular (as shown in Nelson, 1992) when volatility (or covariance) changes are not too gradual.

In light of these considerations, in this paper we treat the covariance matrix of return residuals as observable and construct time series of rolling realized excess square correlations for each asset  $k$ . To that purpose, we estimate  $\hat{e}_{kt}$ ,  $\hat{\delta}_{kt}$ ,

<sup>4</sup> In Section 4, we analyze the robustness of our inference to this and other features of our empirical specification.

<sup>5</sup> See Campbell et al. (1997) for a review of the literature on parametric models of changing volatility.

and  $\hat{\rho}_{knt}^*$  over rolling short-term and long-term intervals of the data of fixed length  $N$  and  $gN$  (with  $g > 1$ ), respectively, according to the following scheme:

$$\begin{array}{c} \overbrace{\left| \begin{array}{ccc} & & \end{array} \right|}^{\hat{e}_{kt}, \text{var}(\hat{e}_{kt})} \\ \dots \left| \begin{array}{ccc} & & \end{array} \right| \dots \\ \underbrace{\left| \begin{array}{ccc} & & \end{array} \right|}_{(\hat{e}_{kt})_{LT}, \text{var}(\hat{e}_{kt})_{LT}} \end{array} \quad (7)$$

In other terms, at each point in time  $t$  and for each asset  $k$ , the model of Eq. (1) is estimated twice, once over the short-term interval  $[t-N+1, t]$  to compute  $\hat{\rho}_{knt}$  as in Eq. (3) for each  $n \neq k$ , and once over the long-term interval  $[t-gN+1, t]$  to compute the adjustment ratio  $\hat{\delta}_{kt}$  and, eventually,  $\hat{\rho}_{knt}^*$  as in Eq. (4) for each  $n \neq k$ . This rolling procedure generates time series of aggregate excess comovement measures  $\{\hat{\rho}_t^*\}_{t=gN}^T$ , which we use in our analysis, without resorting to parametric specifications for the intertemporal dynamics of the covariance matrix of asset returns. Lastly, we need to specify an estimation strategy for the parameters of the linear factor structure of Eq. (1). This is the topic of the next subsection.

## 2.2. Latent comovement

The methodology described above relies on the estimation of the return residuals  $\hat{e}_{kt}$  defined in Eq. (2). These residuals could be estimated separately for each of the available assets by ordinary least squares (OLS). This strategy would however operate under the implicit null hypothesis that the returns  $r_{kt}$ , after controlling for observed block-common and systematic sources of risk, are independent. Hence, OLS estimation may lead to underestimating the extent of excess comovement among those  $\hat{e}_{kt}$ . In this subsection, we propose an alternative estimation strategy that instead uses as its starting point the hypothesis that return residuals do comove beyond what is justified by the observed economic fundamentals  $u_b$  and  $f$ , rather than ignoring that possibility.

The basic intuition of this strategy is to estimate the parameters of Eq. (1) for each asset  $k$  jointly, rather than separately. We start by specifying the following stacked version of the model of Eq. (1) over the interval  $[t-N+1, t]$ :

$$\begin{bmatrix} r_{1t} \\ r_{2t} \\ \vdots \\ r_{Kt} \end{bmatrix} = \begin{bmatrix} F_{1t} & O & \dots & O \\ O & F_{2t} & \dots & O \\ & & \ddots & \\ O & O & \dots & F_{Kt} \end{bmatrix} \begin{bmatrix} B_{1t} \\ B_{2t} \\ \vdots \\ B_{Kt} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{Kt} \end{bmatrix} \quad (8)$$

$$= F_t B_t + e_t, \quad (9)$$

where  $F_{kt} = [1, u_{bt}, f_t]$  is a  $N \times M$  matrix of observed block-common and systematic factors affecting  $r_{kt}$  (in which  $1$  is a  $N \times 1$  unit vector and  $M = N_u + N_f + 1$ ),  $B_{kt} = [\alpha_{kt}, \beta'_{kt}, \gamma'_{kt}]'$  is a  $M \times 1$  vector of factor loadings, and  $O$  is a zero matrix. We further assume that the  $N \times 1$  vectors of disturbances  $e_{kt}$  are uncorrelated across observations, i.e., that  $E[e_{kt}e'_{ns}] = \sigma_{knt}I$  (where  $I$  is a  $N \times N$  identity matrix) if  $t=s$  and  $E[e_{kt}e'_{ns}] = O$  otherwise. This implies that

$$E[e_t e'_t] = V_t = \begin{bmatrix} \sigma_{11t} & \sigma_{12t} & \dots & \sigma_{1Kt} \\ \sigma_{21t} & \sigma_{22t} & \dots & \sigma_{2Kt} \\ & & \ddots & \\ \sigma_{K1t} & \sigma_{K2t} & \dots & \sigma_{KKt} \end{bmatrix} \otimes I \quad (10)$$

$$= \sum_t \otimes I. \quad (11)$$

The above disturbance formulation therefore allows for the parameters controlling for the subsample covariance across assets to vary over time. Efficient estimation of the seemingly unrelated regressions model of Eq. (9) is achieved

via the feasible generalized least squares (FGLS) procedure described, for example, in Greene (1997, pp. 676–688). Because the matrix  $\Sigma_t$  is unknown, OLS residuals can be used to estimate each of its elements consistently as:

$$\hat{\sigma}_{knt}^{\text{OLS}} = \frac{(\hat{e}_{kt}^{\text{OLS}})' \hat{e}_{nt}^{\text{OLS}}}{N}. \quad (12)$$

The FGLS estimator of  $B_t$  is then given by

$$\hat{B}_t^{\text{FGLS}} = \left[ F_t' (\hat{V}_t^{\text{OLS}})^{-1} F_t \right]^{-1} F_t' (\hat{V}_t^{\text{OLS}})^{-1} r_t \quad (13)$$

$$= \left\{ F_t' \left[ \left( \hat{\Sigma}_t^{\text{OLS}} \right)^{-1} \otimes I \right] F_t \right\}^{-1} F_t' \left[ \left( \hat{\Sigma}_t^{\text{OLS}} \right)^{-1} \otimes I \right] r_t, \quad (14)$$

where  $r_t = [r_{1t}, r_{2t}, \dots, r_{Kt}]'$ . The resulting FGLS residuals  $\hat{e}_t^{\text{FGLS}} = r_t - F_t \hat{B}_t^{\text{FGLS}}$  are then used to produce an efficient estimate of each element of the matrix  $\Sigma_t$ ,

$$\hat{\sigma}_{knt}^{\text{FGLS}} = \frac{(\hat{e}_{kt}^{\text{FGLS}})' \hat{e}_{nt}^{\text{FGLS}}}{N}. \quad (15)$$

Finally, the matrix  $\hat{\Sigma}_t^{\text{FGLS}}$  is employed to estimate our measure of asset and market-wide excess comovement

$$\hat{\rho}_{kt}^{\text{FGLS}*} = \frac{1}{N_{kt}} \sum_{\substack{n=1 \\ n \neq k}}^K (\hat{\rho}_{knt}^{\text{FGLS}*})^2 I_{knt} \quad (16)$$

and

$$\hat{\rho}_t^{\text{FGLS}*} = \frac{1}{K} \sum_{k=1}^K \frac{1}{N_{kt}} \sum_{\substack{n=1 \\ n \neq k}}^K (\hat{\rho}_{knt}^{\text{FGLS}*})^2 I_{knt}, \quad (17)$$

respectively, where

$$\hat{\rho}_{knt}^{\text{FGLS}*} = \frac{\hat{\sigma}_{knt}^{\text{FGLS}}}{(\hat{\sigma}_{kkt}^{\text{FGLS}} \hat{\sigma}_{nnt}^{\text{FGLS}})^{\frac{1}{2}} \left\{ 1 + \hat{\delta}_{kt}^{\text{FGLS}} \left[ 1 - \frac{(\hat{\sigma}_{knt}^{\text{FGLS}})^2}{\hat{\sigma}_{kkt}^{\text{FGLS}} \hat{\sigma}_{nnt}^{\text{FGLS}}} \right] \right\}^{\frac{1}{2}}}, \quad (18)$$

$\hat{\delta}_{kt}^{\text{FGLS}} = \frac{\hat{\sigma}_{kkt}^{\text{FGLS}}}{(\hat{\sigma}_{kkt}^{\text{FGLS}})_{LT}} - 1$ , and  $(\hat{\sigma}_{kkt}^{\text{FGLS}})_{LT}$  is obtained from the estimation of  $\Sigma_t$  over the interval  $[t - gN + 1, t]$ . Estimation of  $\hat{\rho}_{knt}^{\text{FGLS}*}$  is repeated for all  $k = 1, \dots, K$  and for each  $t = gN, \dots, T$ , as in the rolling approach of Eq. (7), to generate time series of excess comovement measures  $\{\hat{\rho}_{kt}^{\text{FGLS}*}\}_{t=gN}^T$  and  $\{\hat{\rho}_t^{\text{FGLS}*}\}_{t=gN}^T$ .

### 3. Data

The basic dataset we use in this paper consists of weekly, continuously compounded, dividend-adjusted returns for  $k = 1, \dots, 96$  value-weighted U.S. industry indexes ( $r_{kt}$ ), over the time period January 5, 1976 to December 31, 2001, from Datastream. Datastream classifies approximately 1000 representative companies whose common stocks are traded on the AMEX, NASDAQ, or NYSE by industry based uniquely on their primary activity. Equities with similar industrial classification are then grouped into  $i = 1, \dots, 10$  sectors ( $r_{it}$ ). Finally, Datastream also computes returns for  $s = 1, 2, 3$  macro-sector indexes  $r_{st}$  (Resources, Non Financials excluding Resources, and Financials) and for a broad market index of all sectors ( $r_{mt}$ ). Industry and sector classifications are performed according to definitions provided by the Financial Times Stock Exchange (FTSE) Actuaries.

The choice of the weekly frequency for our database arises from a balance between the different properties of accessible time series. The use of daily equity data in fact raises concerns related to possible biases induced by infrequent and/or nonsynchronous trading, or short-term noise on the resulting statistical inference. Vice versa, monthly



Table 1  
Descriptive statistics

Index	$N$	$\mu$	$\sigma$	Skew	Kurt	$\hat{\rho}_1$	$LB(5)$
Market	3	0.192% <sup>†</sup>	2.31%	−1.62 <sup>†</sup>	21.64 <sup>†</sup>	−0.072 <sup>†</sup>	13.10 <sup>•</sup>
Macro-sectors							
Resources	1	0.157% <sup>•</sup>	2.86%	−0.88 <sup>†</sup>	10.10 <sup>†</sup>	−0.115 <sup>†</sup>	28.10 <sup>†</sup>
Non-Financials	8	0.188% <sup>†</sup>	2.39%	−1.55 <sup>†</sup>	20.46	−0.071 <sup>†</sup>	12.09 <sup>•</sup>
Financials	1	0.243% <sup>†</sup>	2.62%	−0.68 <sup>†</sup>	7.56 <sup>†</sup>	0.015	4.46
Sectors							
Resources	4	0.157% <sup>•</sup>	2.86%	−0.88 <sup>†</sup>	10.10 <sup>†</sup>	−0.115 <sup>†</sup>	28.10 <sup>†</sup>
Basic Industries	9	0.131% <sup>*</sup>	2.90%	−0.79 <sup>†</sup>	14.20 <sup>†</sup>	0.029	7.08
General Industrials	8	0.227% <sup>†</sup>	2.66%	−1.31 <sup>†</sup>	15.62 <sup>†</sup>	−0.017	2.32
Cyclical Consumer Goods	7	0.122% <sup>†</sup>	2.83%	−1.13 <sup>†</sup>	14.77 <sup>†</sup>	−0.006	5.45
Non-Cyclical Consumer Goods	14	0.239% <sup>†</sup>	2.47%	−1.36 <sup>†</sup>	16.20 <sup>†</sup>	−0.087 <sup>†</sup>	13.54 <sup>•</sup>
Cyclical Services	17	0.202% <sup>†</sup>	2.85%	−1.46 <sup>†</sup>	17.57 <sup>†</sup>	−0.030	4.26
Non-Cyclical Services	3	0.156% <sup>•</sup>	2.39%	−1.08 <sup>†</sup>	14.08 <sup>†</sup>	−0.108 <sup>†</sup>	23.58 <sup>†</sup>
Utilities	3	0.096% <sup>*</sup>	1.88%	−0.60 <sup>†</sup>	7.41 <sup>†</sup>	−0.022	5.54
Information Technology	4	0.214% <sup>*</sup>	3.79%	−0.67 <sup>†</sup>	7.15 <sup>†</sup>	−0.072 <sup>†</sup>	14.41 <sup>•</sup>
Financials	13	0.243% <sup>†</sup>	2.62%	−0.68 <sup>†</sup>	7.56 <sup>†</sup>	0.015	4.46

This table reports summary statistics for the time series of weekly returns for the market ( $r_{mt}$ ), the 3 macro-sector indexes ( $r_{st}$ ), and the 10 sector indexes ( $r_{it}$ ) defined in Section 3, over the interval January 5, 1976–December 31, 2001 (1357 observations).  $N$  is the number of sub-category constituents for each index.  $\mu$  is the mean and  $\sigma$  is the standard deviation of each series. *Skew* is the coefficient of skewness, while *Kurt* is the excess kurtosis; their standard errors, in their asymptotic normal distributions, are computed as  $(\frac{6}{N})^{\frac{1}{2}}$  and  $(\frac{24}{N})^{\frac{1}{2}}$ , respectively.  $\hat{\rho}_1$  is the first-order autocorrelation.  $LB(5)$  is the Ljung–Box test of randomness for up to the fifth-order autocorrelation, asymptotically distributed as  $\chi^2[5]$  under the null hypothesis that the series is white noise. A “\*”, “•”, or “†” indicate significance at the 10%, 5%, or 1% level, respectively.

observations may lead us to ignore more rapid cycles of propagation of shocks across fundamentally unrelated assets in the U.S. stock market.

The companies entering each index are selected on the basis of their market capitalization and data availability considerations. Factors like liquidity or cross-holdings are therefore ignored. Datastream also excludes from those indexes such securities as unit trusts, mutual and investment funds, and foreign listings (including ADRs). Index constituents are currently reviewed on an annual basis (in January of each year) to account for declines in market value, takeovers, delistings, changes in the primary business activity, etc.<sup>6</sup> We further eliminate from our dataset 14 industry indexes for which price data were available only for subsets of the sample period. Our final dataset is then made up of 82 industry, 10 sector, 3 macro-sector, and one market return time series of 1357 observations each, which we use in the analysis that follows.

Table 1 presents summary statistics for  $r_{mt}$ , for each  $r_{st}$ , and for each  $r_{it}$ . Not surprisingly, given the growth experienced by the U.S. stock market in the past three decades, most mean weekly returns are positive and significant. The variables are also characterized by little or no skewness and strong and significant leptokurtosis. Index aggregation seems to induce negative return autocorrelation. Indeed, the estimated first-order autocorrelation coefficients  $\hat{\rho}_1$  are not significantly different from zero for many of the sector returns, and the corresponding value for the Ljung–Box portmanteau test for up to the fifth-order serial correlation,  $LB(5)$ , cannot reject the null hypothesis that those  $r_{it}$  are white noise. Similar conclusions can be drawn from the autocorrelation analysis of each of the 82 industry return time series  $r_{kt}$  (not reported here). However,  $\hat{\rho}_1$  is negative and both  $\hat{\rho}_1$  and  $LB(5)$  are statistically significant for the market and for all but the Financials (from Banks to Other Financials) macro-sector returns.

## 4. Empirical analysis

### 4.1. Factor selection

Estimation of Eq. (1) and the seemingly unrelated regressions model of Eq. (9) require the selection of observed block-common and systematic factors for industry returns, i.e., the specification of an observable benchmark. This is a crucial step

<sup>6</sup> Prior to May 1995, indexes were instead reviewed every three months.

in our analysis. Indeed, the test for excess comovement is unavoidably also a test of the validity of the specification we use to control for fundamental comovement, i.e., to compute  $\hat{\rho}_{knt}^{\text{FGLS}*}$  at each point in time  $t$ .<sup>7</sup> The challenge is therefore to design a model that is comprehensive in its scope, general in its structure, and consistent with the “consensus” in the literature.

We start from the variables entering the matrix  $f_t$  in Eq. (1). Fama and French (1992, 1993) find that three observed systematic factors explain a significant portion of the cross-sectional differences in average stock returns. These factors are market risk, book-to-market risk, and small-firm risk. We use these benchmark factors in our regressions. We employ the all-inclusive time series of returns for the market designed by Datastream,  $r_{mt}$ , to proxy for market risk. Fama and French (1993) create mimicking portfolios whose returns proxy for book-to-market risk and small-firm risk. Fama and French (1995) show that both variables are related to economic fundamentals controlling for common risk factors in returns. More specifically, the book-to-market ratio is negatively related to current earnings and positively related to their persistence. Size appears instead to be negatively related to short- and long-term profitability. In the analysis that follows, we use the time series for book-to-market benchmark returns ( $r_{\text{BMT}}$ ) and small-firm benchmark returns ( $r_{\text{SFT}}$ ) available on French’s website.<sup>8</sup>

Sector or macro-sector-specific factors may also explain some of the correlation between our indexes. This correlation may in fact be due not only to market-level, but also to sector-level sources of risk in cash flow innovations. Accordingly, Corsetti et al. (2005) observe that ignoring fluctuations in asset-specific factors may make tests for contagion biased toward rejection. We account for this possibility by specifying a set of block-common factors for each return series  $r_{kt}$ . More specifically, for each of the 82 available indexes, we identify two benchmark sector and macro-sector-portfolios, according to the Datastream industrial classification levels, and use their corresponding weighted average returns ( $r_{it}$  and  $r_{st}$ , respectively) in each of the matrices  $u_b$ .

The final specification of Eq. (1), that we use to control for return covariance driven by fundamentals, is therefore given by

$$r_{kt} = \alpha_{kt} + \beta_{it}^k r_{it} + \beta_{st}^k r_{st} + \gamma_{mt}^k r_{mt} + \gamma_{\text{BMT}}^k r_{\text{BMT}} + \gamma_{\text{SFT}}^k r_{\text{SFT}} + e_{kt}, \quad (19)$$

for each  $k=1, \dots, K$ . Ultimately, the success of our analysis rests on the ability of Eq. (19) to explain each time series of industry returns  $r_{kt}$  and on the ability of the many theories for contagion presented in Section 1 to explain the intertemporal and cross-sectional features of the resulting measures of excess comovement described in Section 2,  $\{\hat{\rho}_t^{\text{FGLS}*}\}_{t=gN}^T$  and other such aggregates. Our evidence reveals that the above model, albeit parsimonious, performs satisfactorily on both counts. This is what we show next.

#### 4.2. FGLS comovement

We start by estimating the model of Eq. (19) over the sample interval January 5, 1976 to December 31, 2001 for all indexes in our database with the FGLS procedure of Section 2.2 across rolling intervals of about two years ( $N=100$ ). We then use the corresponding estimated residuals to compute the unconditional measures of excess comovement described in Section 2.1.

At each point in time  $t$  only conditional correlations that are statistically significant at the 10% level are considered, i.e.,  $\alpha=0.10$  in  $I_{knt}$  of Eq. (5). The correction to those correlations for shifts in conditional volatility, reported in Eq. (4), is implemented by estimating long-term variances of return residuals over a four-year interval ( $g=2$ ). Therefore, the initial  $t=gN$  corresponds to October 29, 1979. We plot the resulting time series  $\{\hat{\rho}_t^{\text{FGLS}*}\}_{t=gN}^T$  in Fig. 1a, together with a benchmark measure of square correlation,  $\{\hat{\rho}_t^{\text{BASE}*}\}_{t=gN}^T$ , computed using the raw return series  $r_{kt}$  (instead of FGLS residuals  $\hat{e}_{kt}^{\text{FGLS}}$ ) in Eqs. (3) to (7) — i.e., accounting for non-stationary return variances but not for the extent and dynamics of returns’ fundamental interdependence by construction — and its conditional equivalent,  $\{\hat{\rho}_t^{\text{BASE}*}\}_{t=gN}^T$ , computed using conditional correlations among those returns. Fig. 1a reveals that the adjustment of Eq. (4) for conditional variance essentially rescales the correlation series  $\hat{\rho}_{knt}$  while preserving their intertemporal dynamics. The upper panel of Table 2 reports summary statistics for  $\hat{\rho}_t^{\text{FGLS}*}$  and  $\hat{\rho}_t^{\text{BASE}*}$ .

<sup>7</sup> E.g., see the discussion in Deb et al. (1996). Some empirical asset pricing studies obviate this problem by estimating latent (i.e., unobserved) factor models in both domestic and international settings (e.g., Bekaert and Hodrick, 1992; Campbell and Hamao, 1992; Pindyck and Rotemberg, 1993; King et al., 1994; Zhou, 1994). Yet, latent-variable modeling raises similar interpretation problems, for it requires assumptions about the joint distribution of observed returns (e.g., Wheatley, 1989) as well as about the “fundamental” nature of the estimated factors.

<sup>8</sup> [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).



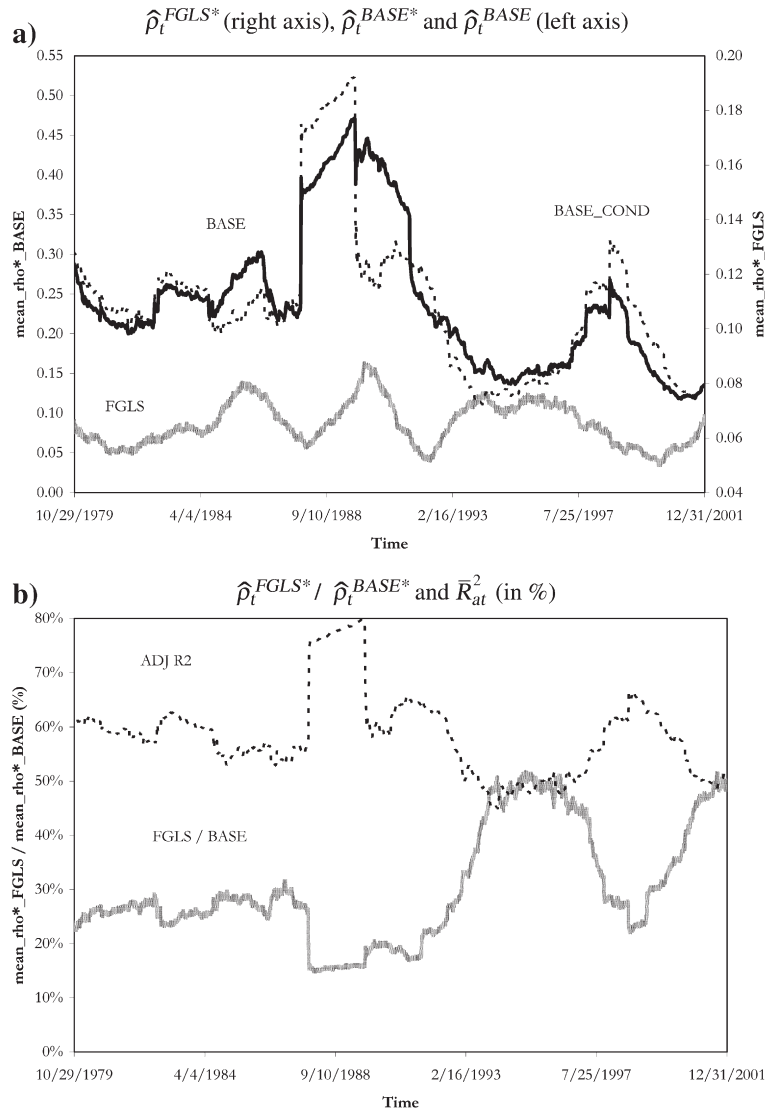


Fig. 1. Mean excess correlation: FGLS procedure. (a) Plots (on the right axis) the time series of mean excess square unconditional correlations  $\hat{\rho}_t^{FGLS*}$  (computed according to the procedure of Section 2.2), a benchmark measure of square unconditional correlation,  $\hat{\rho}_t^{BASE*}$ , computed using raw returns  $r_{kt}$  (instead of estimated residuals  $\hat{e}_{it}^{FGLS}$ ) in Eqs. (3) to (7), and its equivalent,  $\hat{\rho}_t^{BASE}$ , from their square conditional correlations (both on the left axis). (b) Plots (in percentage terms) the ratio between  $\hat{\rho}_t^{FGLS*}$  and  $\hat{\rho}_t^{BASE*}$  (defined in Table 2 as  $R\rho$ ) and  $\bar{R}_{at}^2$ , the mean adjusted  $R^2$  across all industries from the FGLS estimation of Eq. (19).

The FGLS regression based upon of Eq. (19) is quite successful: The mean overall goodness-of-fit measure of McElroy (1977)<sup>9</sup> is greater than 99%, the standard  $F$  test always strongly rejects the null hypothesis that all the slopes in the model are zero, and the mean conventional adjusted  $R^2$  across all industries ( $\bar{R}_{at}^2$  in Fig. 1b) averages about 58% and is never lower than 45% over the entire sample. Yet, our evidence suggests that there is comovement beyond what can be explained by the fundamental model of Section 4.1 in the U.S. stock market. Indeed, excess square correlation  $\hat{\rho}_t^{FGLS*}$  averages about 0.065 — equivalent to an average absolute return residual correlation of  $|\sqrt{\hat{\rho}_t^{FGLS*}}| = 0.255$  — and is statistically different from zero (according to either the  $t$ -square ratio test  $\hat{t}_t^2 = \hat{\rho}_t^{FGLS*} [1 - \hat{\rho}_t^{FGLS*}]^{-1} \sim F[1, N - 2]$  in Table 2 or a standard  $t$ -test for means not reported here) over the entire sample and cross-sectionally at each point in time  $t$ . Excess

<sup>9</sup> This measure is computed as  $R_{st}^2 = 1 - K \{tr[(\hat{\Sigma}_t^{FGLS})^{-1} S_t]\}^{-1}$ , where  $S_t$  is a  $K \times K$  matrix in which  $S_{knt} = N^{-1} r_{kt}' r_{nt} - \bar{r}_{kt} \bar{r}_{nt}$ .

Table 2

Descriptive statistics: FGLS comovement

Index	$\hat{\rho}_t^{\text{FGLS}*}$		$B\rho$	$R\rho$	$T\rho$	$F\rho^{*2}$	$\hat{\rho}_t^{\text{BASE}*}$		$T\rho$	$F\rho^{*2}$
	$\mu$	$\sigma$					$\mu$	$\sigma$		
Market	0.065 <sup>•</sup>	0.008	0.31	27%	16%	17%	0.241 <sup>†</sup>	0.089	90%	90%
Macro-sectors										
Resources	0.089 <sup>†</sup>	0.015	−0.12	60%	16%	17%	0.147 <sup>†</sup>	0.071	70%	71%
Non-Financials	0.073 <sup>†</sup>	0.010	0.43	30%	16%	17%	0.240 <sup>†</sup>	0.093	90%	90%
Financials	0.060 <sup>•</sup>	0.009	0.09	23%	16%	18%	0.265 <sup>†</sup>	0.078	95%	95%
Sectors										
Resources	0.089 <sup>†</sup>	0.015	−0.12	60%	16%	17%	0.147 <sup>†</sup>	0.071	70%	71%
Basic Industries	0.066 <sup>•</sup>	0.014	0.40	25%	15%	16%	0.260 <sup>†</sup>	0.108	92%	92%
General Industrials	0.060 <sup>•</sup>	0.007	0.22	21%	18%	18%	0.287 <sup>†</sup>	0.105	95%	95%
Cyclical Consumer Goods	0.068 <sup>†</sup>	0.012	0.31	27%	17%	18%	0.249 <sup>†</sup>	0.101	93%	93%
Non-Cyclical Consumer Goods	0.060 <sup>•</sup>	0.008	0.28	24%	17%	17%	0.244 <sup>†</sup>	0.109	89%	89%
Cyclical Services	0.054 <sup>•</sup>	0.006	0.22	25%	15%	16%	0.214 <sup>†</sup>	0.076	89%	89%
Non-Cyclical Services	0.094 <sup>†</sup>	0.019	0.36	39%	16%	16%	0.240 <sup>†</sup>	0.090	91%	91%
Utilities	0.099 <sup>†</sup>	0.018	0.13	64%	16%	17%	0.153 <sup>†</sup>	0.078	81%	80%
Information Technology	0.081 <sup>†</sup>	0.025	0.56	29%	17%	18%	0.278 <sup>†</sup>	0.099	92%	92%
Financials	0.060 <sup>•</sup>	0.009	0.09	23%	16%	18%	0.265 <sup>†</sup>	0.078	95%	95%

This table reports summary statistics for the weekly time series of excess square correlation of FGLS residuals ( $\hat{\rho}_t^{\text{FGLS}*}$  in Eq. (6)), estimated according to the procedure described in Section 2 from the specification of Eq. (19), and of benchmark square correlation of gross returns ( $\hat{\rho}_t^{\text{BASE}*}$ ), for the market ( $\hat{\rho}_t^{\text{FGLS}*}$  and  $\hat{\rho}_t^{\text{BASE}*}$ ), the 3 macro-sector indexes ( $\hat{\rho}_{st}^{\text{FGLS}*}$  and  $\hat{\rho}_{st}^{\text{BASE}*}$ ), and the 10 sector indexes ( $\hat{\rho}_{it}^{\text{FGLS}*}$  and  $\hat{\rho}_{it}^{\text{BASE}*}$ ) defined in Section 3, over the interval October 29, 1979–December 31, 2001 (1158 observations).  $B\rho$  is the correlation between each pair  $\hat{\rho}_t^{\text{FGLS}*}$  and  $\hat{\rho}_t^{\text{BASE}*}$ , while  $R\rho$  is the mean ratio between each pair  $\hat{\rho}_t^{\text{FGLS}*}$  and  $\hat{\rho}_t^{\text{BASE}*}$ .  $T\rho$  is the mean percentage of conditional correlations  $\hat{\rho}_{knt}$  significant at the 10% level using the  $t$ -ratio test  $\hat{t}_{knt} = \hat{\rho}_{knt} \left[ \frac{1 - (\hat{\rho}_{knt}^*)^2}{N-2} \right]^{-1/2} \sim t[N-2]$ , for  $N = 100$ , i.e., the mean of market, macro-sector, or sector-wide cross-sectional averages of the industry ratios  $\frac{1}{K-1} \sum_{n=1}^K \frac{1}{n} I_{knt}$ , where, as in Section 2.1,  $I_{knt} = 1$  if  $2 \left[ 1 - \Pr \left\{ |\hat{t}_{knt}| \leq t_{\frac{\alpha}{2}}[N-2] \right\} \right] \leq \alpha$ , with  $\alpha = 0.10$ , and zero otherwise.  $F\rho^{*2}$  is the mean percentage of square unconditional correlations  $(\hat{\rho}_{knt}^*)^2$  significant at the 10% level using the  $t$ -square ratio test  $\hat{t}_{knt}^2 = (\hat{\rho}_{knt}^*)^2 [1 - (\hat{\rho}_{knt}^*)^2]^{-1} (N-2) \sim F[1, N-2]$ , i.e., the mean of market, macro-sector, or sector-wide cross-sectional averages of the industry ratios  $\frac{1}{K-1} \sum_{n=1}^K \frac{1}{n} I_{knt}^2$ , where  $I_{knt}^2 = 1$  if  $[1 - \Pr \{ \hat{t}_{knt}^2 \leq F_{\alpha}[1, N-2] \}] \leq \alpha$ , with  $\alpha = 0.10$ , and zero otherwise. A “\*”, “•”, or “†” indicate that the  $t$ -square statistic  $\hat{\rho}_{knt}^* [1 - \hat{\rho}_{knt}^*]^{-1} (N-2)$  for the test of the null hypothesis  $H_0: \hat{\rho}_{knt}^* = 0$  against the alternative hypothesis  $H_1: \hat{\rho}_{knt}^* > 0$  is significant at the significance at the 10%, 5%, or 1% level, respectively.

unconditional comovement is economically significant as well, for it constitutes almost 30% of the benchmark raw square correlation  $\hat{\rho}_t^{\text{BASE}*}$  (column  $R\rho$  in Table 2).

Excess comovement also fluctuates over time:  $\hat{\rho}_t^{\text{FGLS}*}$  ranges between a minimum of 0.050 and a maximum of 0.087 along relatively long cycles of peaks and troughs. Further, the series  $\hat{\rho}_t^{\text{FGLS}*}$  tends to mimic (although not uniformly across the sample) the behavior of  $\hat{\rho}_t^{\text{BASE}*}$ , as is clear from both Fig. 1a and their (statistically significant) correlation of 0.31 (column  $B\rho$  in Table 2). Market-wide excess square correlation rapidly declines following the adoption of monetary targets by the Federal Reserve (October 9, 1979), remains stable for roughly two years, and then increases steadily toward a peak of 0.079 at the end of 1985; afterwards,  $\hat{\rho}_t^{\text{FGLS}*}$  starts falling well ahead of the Black Monday of October 19, 1987 and reaches a trough of 0.056 in early January 1988. The next cycle of excess comovement, centered in 1990, closely resembles the dynamics of the square unconditional correlations of gross returns. Subsequently, we observe a clear pattern of “decoupling” of  $\hat{\rho}_t^{\text{FGLS}*}$  from  $\hat{\rho}_t^{\text{BASE}*}$ . In particular,  $\hat{\rho}_t^{\text{FGLS}*}$  increases and stays high in the mid to late 1990s, in correspondence with the Internet bubble, while benchmark square correlations drop to near-historical lows before peaking in the summer of 1998. The ensuing decline of excess comovement anticipates the retreat of the stock market, and continues until the first half of 2000;  $\hat{\rho}_t^{\text{FGLS}*}$  increases again in the second half of the year and peaks by the end of the sample period, following the events of September 11, 2001.

Similar conclusions are reached when we examine arithmetic averages of the measures  $\hat{\rho}_{kt}^{\text{FGLS}*}$  (and their corresponding benchmarks  $\hat{\rho}_{kt}^{\text{BASE}*}$ ) across each of the sector aggregations listed in Table 1, i.e.,  $\hat{\rho}_{it}^{\text{FGLS}*}$  and  $\hat{\rho}_{it}^{\text{BASE}*}$  for  $i=1, \dots, 10$  sectors. We display these measures in Fig. 2a to j and report summary statistics in the lower panels of Table 2. There is significant cross-sectional variability in estimates and dynamics of excess square correlation. The

sector with the lowest mean excess comovement is Cyclical Services (from Retailers Soft Goods to Shipping & Ports), with an average  $\hat{\rho}_{it}^{FGLS*}$  of 0.054. Utilities (Electricity, Gas Distribution, and Water) is the index with the highest excess square correlation (0.099). Excess comovement peaks in 1990 and between 1996 and 1997 for many sector grouping, with the notable exception of Utilities and Information Technology (Computer Hardware and Service, Semiconductors, and Telecom Equipment). Those two sectors, together with Non-Cyclical Services (Food and Drug Retailers, Telecom Fixed Line, and Telecom Wireless), also display the widest intertemporal fluctuations for  $\hat{\rho}_{kt}^{FGLS*}$ . Similarly, the span of its cycles varies considerably across sectors and over time, from few months (e.g., in the case of Utilities in the 1980s) to several years, as for the General Industrials index (from Aerospace to Engineering General) between 1992 and 2001.

There is even greater cross-sectional variation in the ratios between  $\hat{\rho}_{it}^{FGLS*}$  and  $\hat{\rho}_{it}^{BASE*}$ , which we interpret as a proxy for the percentage of raw square correlation unexplained by the model of Eq. (19). Indeed, FGLS excess comovement explains from 21% (for General Industrials) to more than 64% (for Utilities) of the indexes' benchmark square correlation. Non-fundamental comovement appears to be especially relevant in the 1990s, as suggested by Fig. 1b. This trend is led by Resources, Basic Industries (from Chemical Commodity to Steel), Cyclical Consumer Goods (from Automobile to Textiles & Leather), and Non-Cyclical Consumer Goods (from Brewers to Retailers-Department Stores), whose measures  $\hat{\rho}_{it}^{FGLS*}$  begins to significantly depart from their bit corresponding  $\hat{\rho}_{it}^{BASE*}$  in 1992. Nevertheless, the ratios for all sectors experience a significant bit increase in 1999, 2000, and 2001.

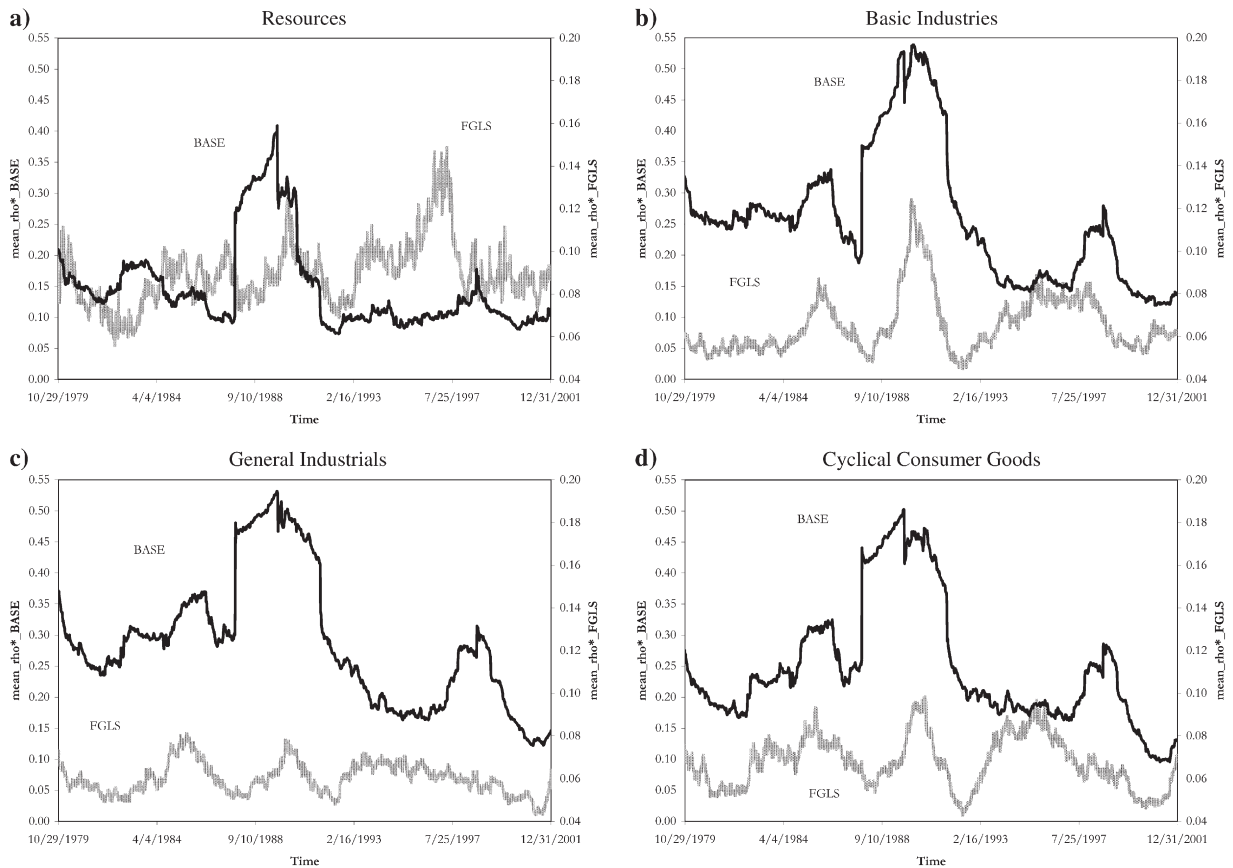


Fig. 2. Mean excess correlation for sectors: FGLS procedure. (a–j) Plot (on the right axis) the time series of mean excess square correlation  $\hat{\rho}_{it}^{FGLS*}$  for each of the 10 sectors listed in Table 1. Each measure is computed as an arithmetic average of the corresponding correlations  $\hat{\rho}_{kt}^{FGLS*}$  (using all  $k \in i$ ), estimated according to the procedure described in Section 2. In each figure, we also plot (on the left axis) a benchmark measure of square correlation,  $\hat{\rho}_{it}^{BASE*}$ , given by the arithmetic average of the corresponding correlations  $\hat{\rho}_{kt}^{BASE*}$  (using all  $k \in i$ ), computed using the raw return series  $r_{kt}$  in Eqs. (3) to (7), instead of the estimated residuals  $\hat{e}_{kt}^{FGLS}$ .

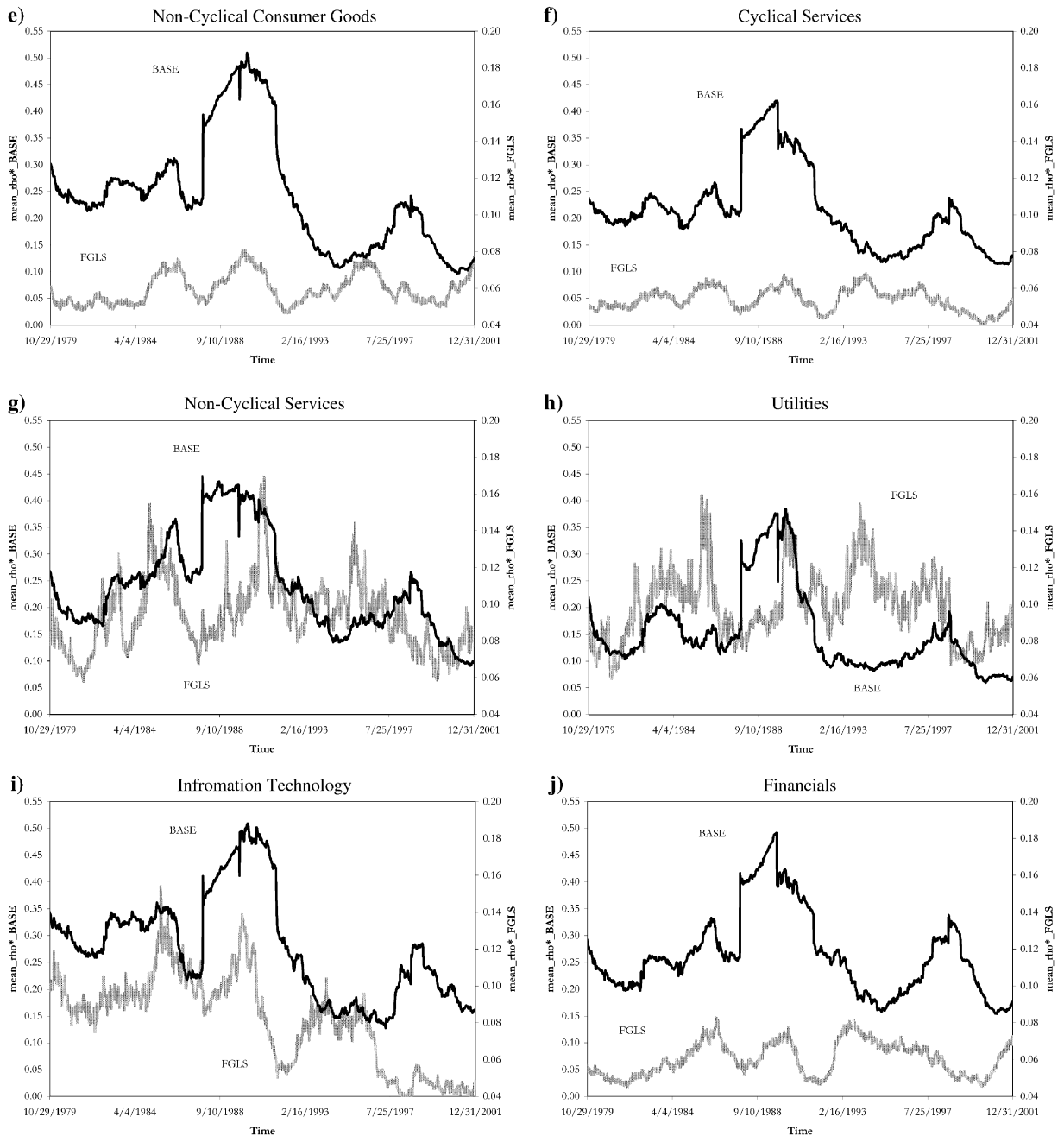


Fig. 2 (continued).

#### 4.3. Robustness tests

In this section we discuss whether any of the main features of the statistical procedure described in Section 2 to measure excess comovement may bias the inference above. We do not report many of the results of this analysis for economy of space. Yet, these results are available on request from the authors.

First, we compute an alternative proxy for excess comovement based on means of excess *absolute* (rather than square) correlations. In other words, we define  $\hat{\rho}_{kt}^*$  in Eq. (5) as being equal to  $\frac{1}{N_{kt}-1} \sum_{n \neq k}^K |\hat{\rho}_{knt}^*| I_{knt}$  and perform all

the subsequent steps in Section 2 accordingly. This alternative definition also prevents excess correlation coefficients of opposite signs from canceling out when averaged across industries; yet, the resulting statistics of doing so are more problematic. Nonetheless, we find that both properties and dynamics of excess absolute residual correlation are qualitatively similar to those displayed by the excess squared residual correlation and described in Section 4.2.

Second, we consider whether the inference above may be driven by sample variation in the estimated correlations of industry return residuals,  $\hat{\rho}_{knt}$ . We preliminarily addressed this issue in Section 2.1 by computing each aggregate measure  $\hat{\rho}_{kt}^{\text{FGLS}*}$  only from statistically significant correlation coefficients at the 10% level ( $\alpha=0.10$ ). Column  $T\rho$  in Table 2 shows that those correlations on average represent 16% of all the upper-diagonal terms in the covariance matrix of residuals  $\hat{\Sigma}_t^{\text{FGLS}}$  defined in Section 2.2, versus a starting point of roughly 90% of  $\hat{\rho}_{knt}^{\text{BASE}}$  among the raw return series  $r_{kt}$ . The percentage of statistically significant conditional correlations from  $\hat{\Sigma}_t^{\text{FGLS}}$  is also considerably stable over the sample:  $T\rho$  never drops below 14% and peaks at 23% only in 1999. As importantly, their corresponding unconditional coefficients of determination  $(\hat{\rho}_{knt}^{\text{FGLS}*})^2$ , in column  $F\rho^{*2}$  of Table 2, are also statistically significant (according to the  $t$ -square ratio test  $\hat{t}_{knt}^2$ ) and with almost identical frequencies across sectors and over time. Finally, the Lagrange multiplier (LM) statistic of Breusch and Pagan (1980) — based on OLS residuals  $(\hat{e}_{kt}^{\text{OLS}})$ :  $\hat{\lambda}_t = N \sum_{k=2}^K \sum_{n=1}^{k-1} (\hat{\rho}_{knt}^{\text{OLS}})^2 \sim \chi^2 \left[ \frac{K(K-1)}{2} \right]$  where  $\hat{\rho}_{knt}^{\text{OLS}} = \frac{\hat{e}_{knt}^{\text{OLS}}}{\hat{\sigma}_{knt}^{\text{OLS}}}$  — leads us to reject the null hypothesis that the matrix  $\hat{\Sigma}_t$  in Eq. (11) is diagonal (at any conventional significance level) in each week  $t$ .

Third, we consider whether accounting for only the statistically significant correlation coefficients  $\hat{\rho}_{knt}$  in Eq. (5) may bias the analysis toward rejection of the null hypothesis of no excess comovement. To that purpose, we repeat the procedure of Section 2 using either a more restrictive ( $\alpha=0.05$ ) or no significance threshold ( $\alpha=1$ ) for the inclusion of excess square pairwise conditional correlations  $(\hat{\rho}_{knt}^*)^2$  in the means  $\hat{\rho}_{kt}^*$  of Eq. (5). In the latter case, the average unconditional coefficient of determination  $\hat{\rho}_t^{\text{FGLS}*}$  is the lowest (0.017, i.e., roughly 7.5% of its corresponding benchmark  $\hat{\rho}_t^{\text{BASE}*}$ ), hence constitutes a lower bound on the extent of excess comovement in the U.S. stock market; in the former case, all measures  $\hat{\rho}_{kt}^{\text{FGLS}}$  are instead higher than those reported in Table 2 and Figs. 1 and 2) (e.g.,  $\hat{\rho}_t^{\text{FGLS}*} = 0.084$  and  $R\rho = 34\%$ ). Nonetheless, in both cases their statistical properties and dynamics are consistent with the inference drawn upon the baseline scenario of Section 4.2 (i.e.,  $\alpha=0.10$ ).

Fourth, we analyze the behavior of our estimate of excess comovement  $\hat{\rho}_t^{\text{FGLS}}$  under the null hypothesis of no financial contagion via simulations. We find that our inference is robust to plausible alternative distributional assumptions of the elliptical class for the return residuals  $e_{kt}$ . Indeed, Monte-Carlo analysis with 10,000 replications of 82 residuals  $e_{kt}$  with 100 observations each shows that our selection procedure based on pairwise  $t$ -ratio tests (Eq. (5)) does not reject the null hypothesis of no excess comovement “too often” (for the chosen  $\alpha=0.10$ ) either under the assumption of i.i.d. normality or under its most popular alternative in the presence of leptokurtic returns (see Table 1), the multivariate  $t$  distribution with no dependence (e.g., Zhou, 1993). In particular, we find that  $T\rho = 9.9967\%$  when the vector  $e_{kt} \sim N(\mathbf{0}, I)$ , where  $\mathbf{0}$  is a zero vector, while  $T\rho = 9.9939\%$  when  $e_{kt} = Z \left( \frac{x_{kk}}{v} \right)^{-\frac{1}{2}}$ , where  $Z \sim N(\mathbf{0}, I)$ ,  $x_{kk} \sim \chi^2[v]$ , and  $v=7$  degrees of freedom.

Fifth, we consider the robustness of our evidence to alternative strategies for the estimation of those return residuals. As previously mentioned, underlying a basic OLS estimation of Eq. (19) is the null hypothesis that index returns  $r_{kt}$  — after controlling for sector and systematic sources of risk — are independent since return residuals would be estimated separately for each industry  $k$ . Vice versa, underlying the FGLS procedure is the null hypothesis that index returns  $r_{kt}$  do comove beyond the degree justified by observed sector and systematic factors since return residuals are estimated jointly for all  $k$ . Because the OLS strategy ignores the possibility that return disturbances  $e_{kt}$  are correlated across securities, the time series  $\hat{\rho}_t^{\text{OLS}*}$  may underestimate the intensity of comovement beyond fundamentals. The FGLS strategy described in Section 2.2 obviates this problem. This approach, however, may also capture latent comovement induced by missing common fundamental factors, if the model of Eq. (19) is misspecified. The resulting measure  $\hat{\rho}_t^{\text{FGLS}*}$  could then overestimate the degree of financial contagion among asset returns. To gauge the extent of this potential bias, we implement the procedure of Section 2 using OLS residuals. The resulting estimates and inference are very similar (both qualitatively and quantitatively) to those based on FGLS residuals.

Lastly, we find that the inference in Section 4.2 is robust to either exclusively employing unadjusted (i.e., conditional) correlations ( $\hat{\rho}_{knt}$  in Eq. (3)) or estimating the adjustment ratio for conditional correlations ( $\hat{\delta}_{kt}$  in Eq. (4)) over several alternative rolling intervals ( $N$  and  $g$ ) for short-term and long-term return volatility. In the latter case, the resulting adjustment for heteroskedasticity may nonetheless be incorrect in the presence of omitted variables or



endogeneity between assets. Unfortunately, no procedure is currently available to control for their impact on  $\hat{\rho}_{knt}^*$ . Yet, according to Forbes and Rigobon (2002), the proposed estimates for unconditional correlation are fairly accurate when assets are “closely connected” (p. 2255). This is the case in our sample, for unconditional correlations of raw returns are both high and statistically significant: E.g., the average  $\hat{\rho}_t^{\text{BASE}*} = 0.241$ ,  $T\rho = 90\%$ , and  $F\rho^{*2} = 90\%$  in Table 2, while the corresponding LM statistic  $\hat{\lambda}_t^{\text{BASE}}$  is strongly statistically significant (at the 1% level or less) in each week  $t$ . Moreover,  $\hat{\rho}_{knt}^*$  systematically underestimates the true unconditional correlation when there is feedback from asset  $n$  to asset  $k$ , biasing the inference toward acceptance, rather than rejection, of the null hypothesis of no excess comovement.

## 5. Explaining excess comovement

The evidence presented in the previous section indicates that a significant portion of return comovement among industry indexes in the U.S. stock market in the past two decades cannot be explained by sector or systematic factors. We also found that our measures of excess square correlation display significant intertemporal and cross-sectional variation, especially when relative to their benchmarks. Perhaps more interestingly, Fig. 1a further shows that raw square correlation is lower in the past decade than in the previous ten years — a statistically significant difference in means of more than seven basis points, i.e., 0.207 versus an average of 0.280 between late 1979 and 1989, consistent with Campbell et al. (2001) — while our estimates of excess comovement are virtually identical (at 0.065), although  $\hat{\rho}_t^{\text{FGLS}*}$  increases by roughly two basis points by the end of the sample. Campbell et al. (2001) argue that this decline in raw correlations may be due to a general decline in the correlation of stock fundamentals. Fig. 1b suggests that non-fundamental comovement played a crucial role in both levels and fluctuations of the correlations among stock indexes during the 1990s and the early 2000s, accounting on average for 35% of  $\hat{\rho}_t^{\text{BASE}*}$  (versus a mean ratio  $R\rho$  of 24% in the 1980s). In addition, these dynamics are consistent with the fluctuations of the mean adjusted  $R^2$  for the FGLS estimation of the fundamental model of Eq. (19): As is clear from Fig. 1b, the variable  $\bar{R}_{at}^2$  and the ratio between  $\hat{\rho}_t^{\text{FGLS}*}$  and  $\hat{\rho}_t^{\text{BASE}*}$  are in fact strongly negatively correlated ( $-0.85$ ) over our sample period. Understanding these phenomena represents therefore one of the priorities for research in financial economics.

In Section 1 we have briefly overviewed the major interpretations for excess comovement proposed by the literature. In the remainder of the paper, we tackle the task of ascertaining the empirical relevance of some of those explanations using our measures of excess square correlation  $\hat{\rho}_t^{\text{FGLS}*}$ . To that purpose, we first develop proxies for information asymmetry and heterogeneity, momentum trading, liquidity shocks, and product market shocks. Then, we discuss the resulting inference at the aggregate and industry level.

### 5.1. Information asymmetry and heterogeneity

Information asymmetry has long been suggested as a cause of comovement among asset prices beyond what would be justified by their fundamentals (King and Wadhvani, 1990; Fleming et al., 1998; Kodres and Pritsker, 2002). In this branch of the literature, the inability to distinguish between idiosyncratic and systematic shocks to those fundamentals leads prices to move together regardless of the underlying structure of the economy. Pasquariello (2007) adds a new dimension to this issue by arguing that greater heterogeneity of investors' information endowments may increase the intensity of excess comovement among returns. The intuition for his result is that market-makers imprecisely learn about the signals and strategic trading activity of speculators sharing information asymmetrically. Incorrect cross-inference about fundamentals and contagion then ensue.

We use market (sector) return volatility  $\sigma_{mt}$  (or  $\sigma_{it}$ ) computed over the interval  $[t - gN + 1, t]$  as a common proxy for the level of market-wide (or sector-wide) information asymmetry or uncertainty at time  $t$  (e.g., Lang and Lundholm, 1993; Leuz and Verrecchia, 2000; Lim, 2001; Zhang, 2006).<sup>10</sup> The dispersion in analysts' earnings forecasts instead represents a widely adopted proxy for information heterogeneity unrelated to risk (e.g., Lang and Lundholm, 1996; Diether et al., 2002; Green, 2004; Pasquariello and Vega, in press). We construct this proxy from the I/B/E/S database

<sup>10</sup> Alternative direct measures of information asymmetry, such as bid-ask spreads (Glosten and Milgrom, 1985), liquidity (Kyle, 1985), or the probability of informed trading (Easley et al., 1996) cannot be estimated over our entire sample period due to data availability constraints.



containing all analysts' annual earnings-per-share (EPS) forecasts between January 1976 and December 2001. For each public firm in the I/B/E/S "US Only" universe, we define diversity of opinion in week  $t$  of any given month as the standard deviation of EPS forecasts made during that month for that firm's "fiscal year one" scaled by the absolute value of the corresponding mean EPS forecast.<sup>11</sup> Alternatively, we measure the degree of disagreement among investors with respect to the value of the traded assets as the ratio of the difference between the highest and the lowest of these forecasts and the absolute value of their corresponding median EPS forecast. We then compute their cross-sectional means and Winsorize them at two standard deviations to obtain two market-wide estimates of information heterogeneity  $H_{1t}$  and  $H_{2t}$ , respectively. According to Pasquariello (2007), more (heterogeneously informed) speculators can more easily disguise their strategic trading activity, increasing equilibrium excess comovement. We account for this additional effect with  $N_t$ , the cross-sectional mean number of analysts providing earnings forecasts for the firms entering  $H_{1t}$  and  $H_{2t}$ .

### 5.2. Momentum trading

Momentum trading (De Bondt and Thaler, 1985, 1987; Jegadeesh and Titman, 1993; Wermers, 1999; Sias, 2004) is another potential explanation of excess comovement. Generalized purchases or sales of assets across sectors or industries, motivated either by herding, imitation, injections and redemptions of cash in mutual funds, the activity of momentum fund managers, or rational or irrational bubbles, may indeed link prices of assets otherwise sharing very little in common.

We test for the validity of this argument by regressing our measures of aggregate and sector-wide excess square correlation on a proxy for market momentum,  $M_t$ , based on size- and value-adjusted mimicking portfolio returns. This variable is available on French's website, yet only at a monthly frequency. Therefore, we consider two additional proxies for momentum. The first is simply the sequence of contemporaneous and lagged returns  $r_{mt-l}$  (or  $r_{it-l}$ ), for  $l=0, 1, 2$ . We also construct momentum dummy variables  $d_{mt}$  and  $d_{it}$ . These variables are equal to one when the sign of the corresponding return  $r_{mt}$  or  $r_{it}$  is the same for the current and each of the previous two weeks, and equal to zero otherwise. In other words, these dummies are positive when either the broad stock market index or the corresponding sector index is experiencing a positive or negative run of length of (at least) three weeks.<sup>12</sup>

### 5.3. Liquidity shocks

Financial contagion has long been related to the dynamics of interest rates. In his empirical analysis of comovement between real stock prices in the U.S. and the U.K., Shiller (1989) finds that a relevant portion of excess price covariance can be explained by positively correlated, extremely time-varying interest rates affecting the values of the traded assets. According to the "correlated liquidity shock channel," excess comovement among asset returns is the result of the trading activity of financially constrained investors. Indeed, Calvo (1999), Kyle and Xiong (2001), and Yuan (2005) argue that short-selling, borrowing, and wealth constraints induce rational speculators to liquidate fundamentally unrelated assets in response to idiosyncratic shocks. These arguments imply that the intensity of financial contagion within and across markets should be greater when interest rates are high or during a bear market or a correction, i.e., when those financial constraints become more binding on traders and speculators.

Alternatively, Fleming et al. (1998), Kodres and Pritsker (2002), and Pasquariello (2007) emphasize how portfolio rebalancing activity by investors, motivated either by risk considerations or strategic motives, may eventually lead equilibrium asset prices to move together beyond the degree justified by underlying systematic factors, but in a symmetric fashion. Along these lines, any variable affecting the costs of rebalancing (transaction fees, bid-ask spreads, and interest rates) should have an impact on the intensity of financial contagion, insofar as it affects the intensity of such rebalancing activity. Higher interest rates increase the opportunity cost of trading in risky assets, the cost of borrowing and shorting, so should reduce the scope of portfolio rebalancing for investors and of the resulting excess comovement.

In this paper we employ  $r_{Ft}$ , a weekly time series of three-month Treasury Bill rates, as a proxy for the time-varying risk-free interest rate. These rates are computed as averages of bid rates quoted by primary dealers in the secondary market and reported to the Federal Reserve Bank of New York at the official close of the U.S. government securities

<sup>11</sup> Each stock must therefore be followed by two or more analysts during that month to be included in the sample.

<sup>12</sup> According to this criterion, the market experienced (positive or negative) runs for 264 weeks over our sample.

Table 3

Market: basic regressions for FGLS comovement

Variables	Regression models											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.0689 <sup>†</sup> (42.18)	0.0650 <sup>†</sup> (156.01)	0.0649 <sup>†</sup> (146.93)	0.0649 <sup>†</sup> (146.93)	0.0679 <sup>†</sup> (79.32)	0.0656 <sup>†</sup> (148.34)	0.0650 <sup>†</sup> (142.76)	0.0590 <sup>†</sup> (42.77)	0.0608 <sup>†</sup> (48.15)	0.0440 <sup>†</sup> (11.70)	0.0418 <sup>†</sup> (11.22)	0.0429 <sup>†</sup> (12.02)
$\sigma_{mt}$	-0.1671 <sup>•</sup> (-2.16)										-0.4711 <sup>†</sup> (-7.70)	-0.4713 <sup>†</sup> (-7.72)
$M_t$		0.0038 (0.41)									0.0048 (0.70)	0.0053 (0.78)
$r_{mt}$		0.0107 (1.18)									-0.0035 (-0.34)	-0.0041 (-0.40)
$r_{mt-1}$		0.0121 (1.27)									-0.0022 (-0.19)	-0.0028 (-0.24)
$r_{mt-2}$		0.0119 (1.28)									-0.0030 (-0.29)	-0.0032 (-0.30)
$d_{mt}$			0.0012* (1.78)									
$d_{mt}^+$				0.0021 <sup>†</sup> (2.69)							0.0016 <sup>•</sup> (2.18)	0.0015 <sup>•</sup> (2.14)
$d_{mt}^-$				-0.0012 (-1.12)							0.00002 (0.02)	-0.00002 (-0.02)
$r_{Ft}$					-0.0423 <sup>†</sup> (-4.06)						-0.0986 <sup>†</sup> (-7.86)	-0.1011 <sup>†</sup> (-8.98)
$d_t^R$						-0.0037 <sup>†</sup> (-3.53)					-0.0002 (-0.24)	-0.0003 (-0.26)
$d_t^T$							0.0003 (0.32)				0.0041 <sup>†</sup> (5.25)	0.0042 <sup>†</sup> (5.87)
$H_{1t}$								0.0259 <sup>†</sup> (4.55)			0.0027 (0.32)	
$H_{2t}$									0.0076 <sup>†</sup> (3.54)			0.0029 (1.39)
$N_t$										0.0026 <sup>†</sup> (5.59)	0.0047 <sup>†</sup> (7.16)	0.0044 <sup>†</sup> (8.09)
$N$	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158
$R_a^2$	1.29%	0.01%	0.29%	0.98%	2.30%	2.49%	-0.06%	3.58%	2.96%	7.08%	23.21%	23.46%

This table reports OLS estimates for the coefficients of the regression of  $\hat{\rho}_t^{\text{FGLS}}$  on various explanatory variables.  $\sigma_{mt}$  is market return volatility over the interval  $[t - gN, t]$ .  $M_t$  is a proxy for market momentum provided by French in his research website.  $r_{mt-l}$  are market returns lagged by  $l$  weeks.  $d_{mt}$  is a dummy variable equal to one if  $\text{sign}(r_{mt}) = \text{sign}(r_{mt-1}) = \text{sign}(r_{mt-2})$  and zero otherwise.  $r_{Ft}$  is the three-month Treasury Bill rate, while  $d_{mt}^+$  ( $d_{mt}^-$ ) is a dummy variable equal to one if  $\text{sign}(r_{mt}) = \text{sign}(r_{mt-1}) = \text{sign}(r_{mt-2}) = +$  ( $-$ ) and zero otherwise.  $d_t^R$  is a dummy variable equal to one if the U.S. economy was in recession in week  $t$  (according to the NBER), and equal to zero otherwise, while  $d_t^T$  is a dummy variable equal to 1 if the Federal Reserve's monetary stance was restrictive in week  $t$ , according to the methodology of Jensen et al. (1996), and equal to zero otherwise. The variables  $H_{1t}$  and  $H_{2t}$  are proxies for the degree of information heterogeneity in the U.S. stock market.  $H_{1t}$  is constructed as the market-wide, cross-sectional mean of the standard deviations of analysts' one-year earnings-per-share (EPS) forecasts in week  $t$ 's month and year (as reported by I/B/E/S) divided by the corresponding mean EPS forecasts, for all companies in the U.S. stock market universe that are followed by two or more analysts during that month.  $H_{2t}$  is instead constructed as the market-wide, cross-sectional mean of the ratios of the differences between analysts' one-year EPS highest and lowest forecasts in week  $t$ 's month and year and the corresponding median EPS forecasts. The resulting series are Winsorized at two standard deviations from their means to obtain  $H_{1t}$  and  $H_{2t}$ . Finally,  $N_t$  is the corresponding market-wide, cross-sectional mean number of analysts covering the I/B/E/S companies used to compute  $H_{1t}$  and  $H_{2t}$  at time  $t$ .  $R_a^2$  is the adjusted  $R^2$ . Statistical significance is evaluated using Newey–West standard errors and the ensuing  $t$ -statistics are shown in parentheses. A “\*”, “•”, or “†” indicate significance at the 10%, 5%, or 1% level, respectively.

market every business day, and are available on the website of the Federal Reserve Board.<sup>13</sup> To test directly for asymmetric contagion, we also devise two additional sets of dummy measures  $d_{mt}^+$  and  $d_{mt}^-$  (and  $d_{it}^+$  and  $d_{it}^-$ , for each  $i = 1, \dots, 10$ ), equal to one if the sign of  $r_{mt}$  ( $r_{it}$ ) over the current and each of the previous two weeks is positive or negative, respectively, and equal to zero otherwise.<sup>14</sup>

<sup>13</sup> <http://www.federalreserve.gov/releases/h15/data/b/tbsm3m.txt>.

<sup>14</sup> According to this criterion, there are 74 weeks of down markets and 190 weeks of up markets in our sample.

Table 4

Sectors: basic regressions for FGLS comovement

Variables	Sectors									
	Resources		Basic Industries		General Industrials		Cyclical Consumer Goods		Non-Cyclical Consumer Goods	
Constant	0.1432 <sup>†</sup> (18.73)	0.1432 <sup>†</sup> (19.14)	0.0604 <sup>†</sup> (8.24)	0.0595 <sup>†</sup> (8.35)	0.0406 <sup>†</sup> (14.13)	0.0436 <sup>†</sup> (15.89)	0.0504 <sup>†</sup> (9.72)	0.0504 <sup>†</sup> (9.73)	0.0488 <sup>†</sup> (11.12)	0.0495 <sup>†</sup> (11.80)
$\sigma_{it}$	-0.8906 <sup>†</sup> (-8.73)	-0.8112 <sup>†</sup> (-8.37)	-0.0148 (-0.12)	0.0101 (0.08)	-0.4780 <sup>†</sup> (-9.04)	-0.5184 <sup>†</sup> (-9.91)	-0.8045* (-5.27)	-0.7328 <sup>†</sup> (-4.75)	0.0401 (0.42)	0.0666 (0.70)
$M_t$	0.0026 (0.28)	0.0043 (0.44)	0.0123 (0.99)	0.0125 (1.01)	0.0074 (1.21)	0.0079 (1.26)	0.0026 (0.21)	0.0038 (0.30)	0.0046 (0.66)	0.0054 (0.78)
$r_{it}$	-0.0061 (-0.53)	-0.0072 (-0.61)	-0.0080 (-0.47)	-0.0083 (-0.49)	-0.0004 (-0.04)	-0.0024 (-0.28)	-0.0166 (-1.20)	-0.0175 (-1.27)	0.0011 (0.12)	0.0014 (0.14)
$r_{it-1}$	-0.0050 (-0.41)	-0.0068 (-0.55)	-0.0047 (-0.28)	-0.0050 (-0.30)	-0.0008 (-0.10)	-0.0029 (-0.33)	-0.0131 (-0.91)	-0.0137 (-0.95)	0.0042 (0.39)	0.0044 (0.43)
$r_{it-2}$	-0.0117 (-0.99)	-0.0115 (-0.97)	-0.0062 (-0.37)	-0.0060 (-0.36)	-0.0031 (-0.42)	-0.0053 (-0.68)	-0.0104 (-0.73)	-0.0099 (-0.70)	-0.0001 (-0.01)	0.0004 (0.04)
$d_{it}^+$	0.0026* (1.94)	0.0027* (2.07)	0.0028* (2.10)	0.0028* (2.10)	0.0009 (1.36)	0.0010 (1.40)	0.0005 (0.33)	0.0005 (0.31)	0.0023 <sup>†</sup> (2.66)	0.0021 <sup>†</sup> (2.58)
$d_{it}^-$	-0.0016 (-1.19)	-0.0018 (-1.32)	-0.0018 (-1.03)	-0.0018 (-0.98)	0.0004 (0.45)	0.00003 (0.04)	-0.0015 (-0.99)	-0.0014 (-0.88)	-0.0027 <sup>†</sup> (-2.83)	-0.0027 <sup>†</sup> (-2.81)
$r_{Ft}$	-0.0479* (-2.05)	-0.0795 <sup>†</sup> (-3.91)	-0.1221 <sup>†</sup> (-5.62)	-0.1316 <sup>†</sup> (-6.43)	-0.0337 <sup>†</sup> (-2.89)	-0.0237* (-2.06)	-0.0889 <sup>†</sup> (-3.44)	-0.1052 <sup>†</sup> (-4.29)	-0.0939 <sup>†</sup> (-6.60)	-0.1007 <sup>†</sup> (-7.83)
$d_t^R$	-0.0023 (-1.46)	-0.0028* (-1.70)	0.0028 (1.30)	0.0026 (1.21)	-0.0046 <sup>†</sup> (-4.30)	-0.0043 <sup>†</sup> (-4.15)	-0.0033* (-1.94)	-0.0036* (-2.07)	0.0018* (2.03)	0.0016* (1.75)
$d_t^T$	0.0055 <sup>†</sup> (4.44)	0.0048 <sup>†</sup> (3.82)	0.0077 <sup>†</sup> (4.90)	0.0072 <sup>†</sup> (4.82)	0.0020 <sup>†</sup> (2.62)	0.0028 <sup>†</sup> (3.91)	0.0065 <sup>†</sup> (4.17)	0.0058 <sup>†</sup> (4.02)	0.0039 <sup>†</sup> (4.37)	0.0036 <sup>†</sup> (4.19)
$H_{1t}$	0.0460 <sup>†</sup> (3.36)		0.0178 (1.33)		-0.0213 <sup>†</sup> (-2.92)		0.0328* (2.48)		0.0131 (1.46)	
$H_{2t}$		0.0112 <sup>†</sup> (3.62)		0.0025 (0.70)		0.0008 (0.37)		0.0084* (2.43)		0.0050* (2.08)
$N_t$	-0.0048 <sup>†</sup> (-4.12)	-0.0042 <sup>†</sup> (-4.24)	0.0007 (0.66)	0.0012 (1.25)	0.0048 <sup>†</sup> (9.00)	0.0037 <sup>†</sup> (7.93)	0.0045 <sup>†</sup> (4.14)	0.0047 <sup>†</sup> (4.68)	0.0014* (1.85)	0.0013* (2.11)
$N$	1158	1158	1158	1158	1158	1158	1158	1158	1158	1158
$R_a^2$	29.25%	29.09%	7.61%	7.42%	24.72%	23.47%	12.81%	12.68%	14.14%	14.52%
Variables	Sectors									
	Cyclical Services		Non-Cyclical Services		Utilities		Information Technology		Financials	
Constant	0.0298 <sup>†</sup> (11.92)	0.0315 <sup>†</sup> (12.82)	0.0320 <sup>†</sup> (3.77)	0.0291 <sup>†</sup> (3.48)	0.0523 <sup>†</sup> (5.84)	0.0552 <sup>†</sup> (6.67)	-0.0515 <sup>†</sup> (-5.52)	-0.0433 <sup>†</sup> (-5.10)	0.0565 <sup>†</sup> (16.60)	0.0594 <sup>†</sup> (18.40)
$\sigma_{it}$	-0.3661 <sup>†</sup> (-9.31)	-0.3791 <sup>†</sup> (-9.48)	-0.2837 (-1.47)	-0.3388* (-1.89)	-0.6002* (-2.44)	-0.8747 <sup>†</sup> (-3.73)	-0.8683 <sup>†</sup> (-10.47)	-0.8572 <sup>†</sup> (-11.11)	-0.7049 <sup>†</sup> (-11.00)	-0.7343 <sup>†</sup> (-11.26)
$M_t$	0.0005 (0.09)	0.0008 (0.16)	0.0065 (0.36)	0.0041 (0.23)	0.0145 (0.95)	0.0108 (0.69)	0.0037 (0.30)	0.0083 (0.70)	-0.0016 (-0.23)	-0.0012 (-0.17)
$r_{it}$	0.0014 (0.26)	0.0008 (0.14)	0.0144 (0.65)	0.0182 (0.83)	-0.0365 (-1.24)	-0.0397 (-1.34)	-0.0114 (-1.17)	-0.0131 (-1.37)	-0.0113 (-1.31)	-0.0114 (-1.31)
$r_{it-1}$	0.0015 (0.27)	0.0009 (0.15)	0.0125 (0.54)	0.0165 (0.72)	-0.0127 (-0.42)	-0.0151 (-0.51)	-0.0080 (-0.76)	-0.0098 (-0.94)	-0.0092 (-0.95)	-0.0090 (-0.92)
$r_{it-2}$	0.0029 (0.53)	0.0022 (0.39)	0.0034 (0.16)	0.0066 (0.31)	-0.0163 (-0.58)	-0.0217 (-0.76)	-0.0084 (-0.83)	-0.0090 (-0.91)	-0.0123 (-1.37)	-0.0121 (-1.31)
$d_{it}^+$	-0.0004 (-0.81)	-0.0004 (-0.67)	0.0021 (0.97)	0.0021 (0.99)	0.0008 (0.46)	0.0015 (0.88)	0.0022 (1.38)	0.0026 (1.64)	0.0020* (2.40)	0.0020* (2.38)
$d_{it}^-$	0.0001 (0.12)	-0.0001 (-0.11)	-0.0024 (-1.34)	-0.0019 (-1.06)	0.0007 (0.36)	0.0004 (0.21)	-0.0017 (-1.01)	-0.0018 (-1.15)	0.0013 (1.34)	0.0013 (1.31)
$r_{Ft}$	-0.0501 <sup>†</sup> (-5.13)	-0.0451 <sup>†</sup> (-5.73)	-0.2579 <sup>†</sup> (-6.94)	-0.2422 <sup>†</sup> (-6.38)	-0.2104 <sup>†</sup> (-5.67)	-0.1760 <sup>†</sup> (-4.81)	0.0952 <sup>†</sup> (3.34)	0.0700 <sup>†</sup> (2.77)	-0.2240 <sup>†</sup> (-16.88)	-0.2180 <sup>†</sup> (-18.61)
$d_t^R$	-0.0011* (-2.03)	-0.0010* (-1.90)	0.0053 (1.46)	0.0056 (1.57)	-0.0042* (-1.83)	-0.0032 (-1.52)	-0.0020 (-1.01)	-0.0023 (-1.32)	0.0001 (0.09)	0.0002 (0.24)

(continued on next page)

Table 4 (continued)

	Cyclical Services		Non-Cyclical Services		Utilities		Information Technology	Financials		
$d_t^T$	0.0006 (1.13)	0.0010 <sup>•</sup> (2.11)	−0.0001 (−0.04)	0.0002 (0.07)	−0.0046 <sup>•</sup> (−2.17)	−0.0031 <sup>*</sup> (−1.67)	0.0091 <sup>†</sup> (5.96)	0.0096 <sup>†</sup> (7.45)	0.0033 <sup>†</sup> (4.32)	0.0038 <sup>†</sup> (5.59)
$H_{1t}$	−0.0110 (−1.65)		−0.0302 (−1.47)		−0.0715 <sup>†</sup> (−3.37)		0.0341 <sup>•</sup> (2.17)		−0.0159 <sup>*</sup> (−1.80)	
$H_{2t}$		0.0007 (0.54)		−0.0141 <sup>•</sup> (−2.57)		−0.0185 <sup>†</sup> (−3.74)		0.0261 <sup>†</sup> (5.87)		0.0007 (0.31)
$N_t$	0.0050 <sup>†</sup> (9.70)	0.0044 <sup>†</sup> (10.00)	0.0114 <sup>†</sup> (8.49)	0.0118 <sup>†</sup> (9.64)	0.0112 <sup>†</sup> (7.73)	0.0102 <sup>†</sup> (8.70)	0.0180 <sup>†</sup> (13.78)	0.0162 <sup>†</sup> (14.92)	0.0048 <sup>†</sup> (7.30)	0.0040 <sup>†</sup> (7.33)
$N$	1158	1158	1158	1158	1158	1158	1158	1158	1158	1158
$R_a^2$	28.82%	28.33%	19.48%	20.26%	19.63%	19.64%	70.71%	72.76%	40.33%	39.88%

This table reports OLS estimates for the coefficients of the regressions of  $\hat{\rho}_{it}^{\text{FGLS}*}$  on various explanatory variables for each of the 10 sectors listed in Table 1.  $\sigma_{it}$  is sector  $i$  return volatility over the interval  $[t - gN, t]$ .  $M_t$  is a proxy for market momentum provided by French in his research website.  $r_{it-1}$  are sector  $i$  returns lagged by  $l$  weeks.  $d_{it}$  is a dummy variable equal to one if  $\text{sign}(r_{it}) = \text{sign}(r_{it-1}) = \text{sign}(r_{it-2})$  and zero otherwise.  $r_{Ft}$  is the three-month Treasury Bill rate, while  $d_{it}^+$  ( $d_{it}^-$ ) is a dummy variable equal to one if  $\text{sign}(r_{it}) = \text{sign}(r_{it-1}) = \text{sign}(r_{it-2}) = +$  ( $-$ ) and zero otherwise.  $d_{it}^R$  is a dummy variable equal to one if the U.S. economy was in recession in week  $t$  (according to the NBER), and equal to zero otherwise, while  $d_{it}^T$  is a dummy variable equal to 1 if the Federal Reserve's monetary stance was restrictive in week  $t$ , according to the methodology of Jensen et al. (1996), and equal to zero otherwise. Finally, the variable  $H_t$  is a proxy for the degree of information heterogeneity in the U.S. stock market. The variables  $H_{1t}$  and  $H_{2t}$  are proxies for the degree of information heterogeneity in the U.S. stock market.  $H_{1t}$  is constructed as the market-wide, cross-sectional mean of the standard deviations of analysts' one-year EPS forecasts in week  $t$ 's month and year (as reported by I/B/E/S) divided by the corresponding mean EPS forecasts, for all companies in the U.S. stock market universe that are followed by two or more analysts during that month.  $H_{2t}$  is instead constructed as the market-wide, cross-sectional mean of the ratios of the differences between analysts' one-year EPS highest and lowest forecasts in week  $t$ 's month and year and the corresponding median EPS forecasts. The resulting series are Winsorized at two standard deviations from their means to obtain  $H_{1t}$  and  $H_{2t}$ . Finally,  $N_t$  is the corresponding market-wide, cross-sectional mean number of analysts covering the I/B/E/S companies used to compute  $H_{1t}$  and  $H_{2t}$  at time  $t$ .  $R_a^2$  is the adjusted  $R^2$ . Statistical significance is evaluated using Newey–West standard errors and the ensuing  $t$ -statistics are shown in parentheses. A “\*”, “•”, or “†” indicate significance at the 10%, 5%, or 1% level, respectively.

#### 5.4. Product market shocks

In a recent paper, Pavlova and Rigobon (2007) show that output or productivity shocks can induce contagion among fundamentally unrelated markets. The intuition of their model is that an output shock to one asset alters consumers' relative demand for other assets, hence the prices of the corresponding financial claims.<sup>15</sup> Albeit symmetric in principle, such contagion should nonetheless be more intense in states of the world when those shocks are more likely to occur, i.e., during either recessions or expansions. We define U.S. economic conditions using the business cycle dates provided by the National Bureau of Economic Research (NBER).<sup>16</sup> NBER expansions (recessions) begin at the trough (peak) of the cycles and end at the peak (trough). We then construct a dummy  $d_{it}^R$  equal to one if week  $t$  falls into a month of recession, and equal to zero otherwise. In our sample, economic contractions had shorter duration than expansions, and  $d_{it}^R = 1$  for just 165 of the 1,158 weeks for which  $\hat{\rho}_{it}^{\text{OLS}*}$  and  $\hat{\rho}_{it}^{\text{FGLS}*}$  have been estimated.

Excess comovement may also be related to the monetary policy of the Federal Reserve. Many studies report direct and indirect evidence of a link between monetary policy and economic activity.<sup>17</sup> Therefore, changes in the monetary stance of a Central Bank can be regarded as signaling (or even inducing) present and future real output shocks to the economy or to the sectors most sensitive to it. Furthermore, financial constraints are more likely to affect the portfolio choices of investors during restrictive monetary regimes. We measure the stringency of U.S. monetary policy by using changes in the discount rate, as in Waud (1970), Laurent (1988), and Jensen et al. (1996). More specifically, we define expansionary monetary environments as periods of declining Federal Reserve discount rates and tight monetary environments as those characterized by rising discount rates. Finally, we construct a dummy  $d_{it}^T$  equal to one if week  $t$  falls into a month of restrictive monetary policy, and equal to zero otherwise.<sup>18</sup> Monetary contractions were more

<sup>15</sup> Pavlova and Rigobon (2007) use this intuition to explain excess comovement among international financial markets.

<sup>16</sup> These dates are reported in the NBER's website, [www.nber.org/cycles.html](http://www.nber.org/cycles.html).

<sup>17</sup> See Jensen et al. (1996) for a review.

<sup>18</sup> Jensen et al. (1996) show that the resulting indicator is highly correlated with the dynamics of alternative proxies for the stance of the Federal Reserve's monetary policy, such as the monetary base, adjusted-Fed-credit, excess reserves, and the federal funds premium (calculated as the difference between the federal funds rate and the three-month Treasury Bill rate).

frequent than recessions over the sample period, since they occurred for 453 weeks between October 29, 1979 and December 31, 2001.

### 5.5. Aggregate time-series results

To determine the relevance of these considerations at the aggregate level, we regress our measure of excess square correlation within the U.S. stock market ( $\hat{\rho}_t^{\text{FGLS}*}$ ) on each of the above proxies, first separately (models (1) to (10) in Table 3) and then jointly (models (11) and (12) in Table 3). Regressions are estimated via OLS, but we evaluate the statistical significance of the coefficients' estimates with Newey–West standard errors to correct for heteroskedasticity and autocorrelation.<sup>19</sup>

In general, the variables devised in Sections 5.1 to 5.4 perform satisfactorily in explaining the dynamics of excess comovement within the U.S. stock market in the last two decades. The adjusted  $R^2$  is greater than 23% for both the full regressions of models (11) and (12). Information heterogeneity among traders is the single most relevant source of excess comovement in our sample. Indeed, dispersion of analysts' EPS forecasts (measured by either  $H_{1t}$  or  $H_{2t}$ ) and their corresponding number ( $N_t$ ) account for a significant portion of variability in excess square unconditional correlation measured with FGLS residuals. The coefficients for these variables are positive (hence in the direction suggested by the theory) and strongly significant (at the 1% level or less), generating an adjusted  $R^2$  of about 4% for  $H_{1t}$ , 3% for  $H_{2t}$ , and 7% for  $N_t$ . Interestingly, even after controlling for information heterogeneity, greater market volatility  $\sigma_{mt}$  has a negative, statistically significant impact on excess comovement (columns (1), (11), and (12) in Table 3), contrary to the predictions of the literature (e.g., Kodres and Pritsker, 2002).<sup>20</sup>

This evidence provides some support to the notion, introduced by Pasquariello (2007), that information asymmetry is just a necessary but not a sufficient condition for excess comovement among equilibrium asset prices. Moreover, in his setting, greater market volatility improves the relative precision of traders' signals, hence not only inducing greater revisions of their beliefs (as argued by Connolly and Wang, 2000) but improving their cross-asset inference as well. Thus, according to Table 3, when  $\sigma_{mt}$  is higher the latter effect prevails over the former, and  $\hat{\rho}_t^{\text{FGLS}*}$  declines.

Overall, these results suggest a role for the portfolio rebalancing activity of investors, albeit motivated by strategic considerations rather than risk, in explaining pervasive intra-market contagion. Consistent with this assertion, excess comovement in our sample turns out to be only a weakly asymmetric phenomenon. When dummy variables  $d_{mt}^+$  and  $d_{mt}^-$  are included in the regressions of Table 3 (models (4), (11), and (12)), we find that excess square correlation increases by only about 0.2 basis points during market upturns, while coefficients for  $d_{mt}^-$  are not statistically different from zero. The lack of (or the presence of economically insignificant) asymmetry in  $\hat{\rho}_t^{\text{FGLS}*}$  is unfavorable to theories of contagion relying on the role of financial and wealth constraints, that are more binding during market downturns.

A further test for liquidity-based theories of financial contagion comes from the inclusion of short-term interest rates in the analysis. The correlated liquidity shock channel implies that excess correlation should be greater when  $r_F$  is higher. The resulting evidence is again unconvincing. Estimates from these regressions are reported in columns (5), (11), and (12) of Table 3. The coefficient for  $r_{Ft}$  on  $\hat{\rho}_t^{\text{FGLS}*}$  is negative and strongly significant, and the adjusted  $R^2$  for model (5) is about 2.3%. Additionally, both sign and statistical significance are preserved even after including all the other proxies. Higher interest rates may reduce the extent of excess comovement in the U.S. stock market because they represent a greater opportunity cost of re-balancing portfolios of risky assets (as argued in Section 5.3). Based on this evidence, liquidity shocks appear to have no explanatory power for our measures of excess square correlation.

Market momentum is equally insignificant (see column (2) in Table 3), as are contemporaneous and lagged returns, regardless of whether we control for positive and negative market runs for  $\hat{\rho}_t^{\text{FGLS}*}$  (models (11) and (12)). Consistently, Wald statistics for the joint hypothesis that all the corresponding coefficients are equal to zero (not reported here) are always insignificant in both specifications. The coefficient for the dummy for existing market trend ( $d_{mt}$ ) is statistically significant (at the 10% level) in the regressions for  $\hat{\rho}_t^{\text{FGLS}*}$  (column (3) in Table 3). However,

<sup>19</sup> E.g., King et al. (1994) and Carrieri et al. (2006), among others, estimate linear regressions whose dependent variables are correlation coefficients. Inference from these regressions may be biased since both  $\hat{\rho}_t^{\text{FGLS}*}$  and  $\hat{\rho}_{it}^{\text{FGLS}*}$  are strictly between zero and one in our sample (e.g., see the discussion in Papke and Wooldridge, 1996). Nonetheless, the estimation of either corresponding regression models for *logit* transformations mapping either dependent variable to the real line — i.e., for  $\ln\left(\frac{\hat{\rho}_t^{\text{FGLS}*}}{1-\hat{\rho}_t^{\text{FGLS}*}}\right)$  and  $\ln\left(\frac{\hat{\rho}_{it}^{\text{FGLS}*}}{1-\hat{\rho}_{it}^{\text{FGLS}*}}\right)$  (e.g., Greene, 1997, pp. 894–896) — via OLS or generalized linear models with a logit link and the binomial family via quasi-maximum likelihood — the approach proposed by Papke and Wooldridge (1996) — leads to virtually identical inference. This analysis is available on request from the authors.

<sup>20</sup> We obtain similar results when using rolled short-term return volatility series, i.e., computed over the shorter interval  $[t-4+1, t]$ .



according to model (3), excess square correlation increases by only 0.1 basis points during prolonged market swings. Non-fundamental comovement is instead sensitive to fluctuations in the U.S. economy. In particular, column (6) in Table 3 shows that  $\hat{\rho}_t^{\text{FGLS}*}$  declines by 0.37 basis points when  $d_t^R=1$ , but increases by about 0.41 basis points when  $d_t^T=1$ , although only after controlling for fluctuations in interest rates (models (11) and (12)). Therefore, excess comovement is (almost symmetrically) greater during expansions and the monetary contractions generally accompanying them. We interpret these findings as consistent with the view that both positive and negative real output shocks induce financial contagion among unrelated industries in our sample.

### 5.6. Industry time-series results

We now investigate the ability of information, momentum, liquidity, and product market shocks to explain excess comovement at the industry level. We regress the time series of excess absolute correlation for each of the ten sectors in Table 1 (displayed in Fig. 2) on all the proxies described in Sections 5.1 to 5.4 (as in models (11) and (12) of Table 3) and report estimated coefficients in Table 4.

Consistent with the aggregate results of Table 3, information asymmetry, information heterogeneity, and real output shocks uniformly explain a significant portion of sector averages  $\hat{\rho}_{it}^{\text{FGLS}*}$ . However, the explanatory power of those regressions varies considerably across sectors, ranging from the lows of Basic Industries (8%) and Cyclical Consumer Goods (13%) to the highs of Information Technology (over 70%) and Financials (40%). The interaction of lower long-term sector volatility ( $\sigma_{it}$ ) and greater asymmetric sharing of information among analysts (either  $H_{1t}$  or  $H_{2t}$  and  $N_t$ ), by fostering incorrect cross-asset inference, increases the non-fundamental comovement for most sectors, except the Basic Industries grouping.<sup>21</sup> Excess square sector correlation is also contingent on the state of the U.S. economy:  $\hat{\rho}_{it}^{\text{FGLS}*}$  is lower during recessions or bit more expansive monetary conditions, especially for General Industrials and Information Technology, respectively.

Momentum ( $M_t$ ) and contemporaneous and lagged returns are never significant in the regressions of Table 4. Accordingly, unreported Wald tests cannot reject the joint null hypothesis that all the corresponding coefficients are equal to zero.<sup>22</sup> Similarly, the sector dummies  $d_{it}$  for unsigned return runs of at least three weeks (whose coefficients are not reported here) again play no role in the dynamics of  $\hat{\rho}_{it}^{\text{FGLS}*}$ . Once more, we find no evidence that excess comovement in bit our sample is related to liquidity shocks: Most time series of excess square sector correlation are symmetric and, save for the Information Technology index, negatively related to the level of short-term interest rates. Indeed, the coefficients for sector performance dummies  $d_{it}^+$  and  $d_{it}^-$  are either statistically insignificant or economically trivial (between 0.2 and 0.3 basis points) for short-term upward trends in the corresponding indexes. These estimates suggest that protracted signed runs in sector returns do not affect the degree of sector-wide excess comovement, analogously to the market-wide results reported in Table 3.<sup>23</sup>

Overall, and despite some strong cross-sectional variation, market (and sector) volatility, dispersion of analysts' earnings forecasts, and monetary and real output developments contribute substantially to the fluctuations in our measures of excess square correlation. Nevertheless, the positive and strongly significant constant terms in all of the above regressions of Tables 3 and 4 and the disappointing results of momentum, contemporaneous and lagged returns, and market trends suggest that much more of the excess comovement we find in the U.S. stock market remains to be explained.

<sup>21</sup> As in Section 5.5, the coefficients for  $H_{1t}$  and  $H_{2t}$ , albeit positive and significant in univariate regressions on  $\hat{\rho}_{it}^{\text{FGLS}*}$  (not reported here), become insignificant or negative after introducing  $N_t$ .

<sup>22</sup> In unreported analysis, the inclusion of market momentum  $M_t$  as an observed systematic source of risk (e.g., Lewellen, 2002) in the linear factor model of Eq. (19) does not meaningfully affects our inference.

<sup>23</sup> We also test for whether the turn-of-the-year effect of Banz (1981), Blume and Stambaugh (1983), Keim (1983), and Roll (1983) may contribute to the estimated excess comovement among U.S. equity indexes. Specifically, there is strong evidence that stocks with small market capitalization tend to outperform stocks with large market capitalization between the end of December and the beginning of January. This phenomenon is commonly attributed to individual and institutional investors attempting to realize a fiscal gain by selling stocks that have declined during the year before buying them back in January (Roll, 1983), or parking the proceeds of such sales that were not immediately reinvested (Ritter, 1988). Such activity may drive upward the return comovement of the traded stocks in December and/or January as well. We test this hypothesis by augmenting models (11) and (12) in Tables 3 and 4 for  $\hat{\rho}_t^{\text{FGLS}*}$  and  $\hat{\rho}_{it}^{\text{FGLS}*}$ , respectively, with a calendar dummy  $TOY_t$  equal to one if week  $t$  is in December or January and zero otherwise. The inclusion of  $TOY_t$  has no effect on the inference above and none of the corresponding coefficients (not reported here) is statistically different from zero.



## 6. Conclusions

This study investigates one of the most fundamental aspects of asset pricing, the comovement of security prices, focusing on the degree to which observed correlations cannot be explained by fundamental factors. It has presented an empirical analysis of excess comovement in a sample of 82 industry indexes for the U.S. equity market over the interval January 5, 1976 to December 31, 2001. Excess correlation is defined here as the square unconditional, statistically significant correlation of the estimated residuals from joint (FGLS) rolling regressions of industry returns on observed fundamental sources of risk, specifically sector groupings and the three Fama-French factors.

Our analysis showed that aggregate excess square correlation is both economically and statistically significant, averaging 0.07 over our entire sample (which translates into a mean absolute residual correlation of 0.26) and representing roughly 30% of the average raw square return correlation. Excess comovement is also uniformly significant across all industries over the entire time interval and for between 14% and 23% of all return residual correlations at any given time. Furthermore, our results suggest that non-fundamental comovement has been playing an increasingly important role in affecting the covariance among stock indexes, especially during the 1990s and the early 2000s.

We also analyzed the determinants of this excess comovement. We found that excess square correlation is positively related to the dispersion and copiousness of analysts' earnings forecasts, negatively related to market volatility and the level of the short-term interest rate, and often dependent upon the state of the U.S. economy. These variables explain more than 23% of the fluctuations in market-wide, and up to 73% of the variation in sector-wide excess comovement estimated using FGLS residuals. These results are remarkably uniform across industries, despite some notable exceptions (e.g., the Information Technology index). In addition, most estimated indicators of excess comovement are symmetric, i.e., not (statistically or economically) significantly different in rising or falling markets. This evidence supports the theoretical literature attributing financial contagion to the portfolio rebalancing decisions of investors, to the heterogeneity of their information endowments, or to product market shocks, but also suggests that excess comovement in the U.S. stock market does not stem from liquidity shocks.

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