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Forthcoming in Empirical Economics

Abstract

The aim of this paper is to analyze the relationships between common shocks affecting the real economy and those underlying co-fluctuations in U.S. financial markets. In order to do this, we test for links between these common factors and also use the econometric theory of non-stationary panel data to estimate the relationships. The estimates prove the existence of significant relationships between financial and macroeconomic factors. It is also shown that there are forces pulling U.S. financial markets to move.

Keywords

PANIC analysis Panel Data Common factors Financial Crises U.S

Classification JEL

C5 . C23 . D1 . G1 . N12

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Forthcoming in Empirical Economics

Abstract The aim of this paper is to analyze the relationships between common shocks affecting the real economy and those underlying co-fluctuations in U.S. financial markets. In order to do this, we test for links between these common factors and also use the econometric theory of non-stationary panel data to estimate the relationships. The estimates prove the existence of significant relationships between financial and macroeconomic factors. It is also shown that there are forces pulling U.S. financial markets to move with the real economy, as seen through nearly instantaneous adjustment to a new equilibrium.

Keywords PANIC analysis · Panel Data · Common factors · Financial Crises · U.S

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1 Introduction

The bursting of the bubble in U.S. financial markets in 2008 forced some of the largest and most vulnerable banks and insurance companies in the U.S. to declare bankruptcy or seek financial aid. Market confidence decreased sharply and despite many efforts, the U.S. economy inevitably plunged into recession. In order to gain an understanding of likely developments in this economy, it is important to know which links actually exist between financial markets and the real economy in the U.S. This study aims to analyze these links, targeting key areas of the U.S. economy such as manufacturing, housing and employment. The analysis will also address the relationship between the accumulation of twin deficits and the state of U.S. financial markets. Specifically, we will

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discuss the relationships between the common factors responsible for co-fluctuations between macroeconomic data series and the variables identified as factors observed in financial markets.

The use of observed variables as proxies for underlying factors is becoming an increasingly common practice. This approach was used by Chen et al. (1986) who, in the context of arbitrage pricing theory, show that unobserved financial factors are related to inflation. The three factors that we adopt are those of Fama and French (1993). We use the Bai and Ng (2006) test to look for relations between the common factors in the different sectors of the U.S. economy. These common factors are estimated using principal component analysis. Thus, we use a factor model to capture the co-movements between each of these sectors being considered. The use of factor models to account for common factors was initially developed by Burns and Mitchell (1946). This strategy has also been used by a number of other authors in their study of sectoral co-movements, including Lilien (1982), Chamberlain and Rothschild (1983), Davis and Haltiwanger (1992), Croux et al. (2001) and Dufrenot et al. (2007). This type of analysis allows us to account for the importance of co-movements between macroeconomic data series, such that the dynamics of each variable can be represented as the sum of a common component and an idiosyncratic term.

To estimate the relationship between financial markets and the real economy in the U.S., we will also use the properties of non-stationary time series in panel data and a set of methodologies which address the key concepts of cointegration and error correction models.

In the next section of the paper, we briefly present the state of the U.S. financial system, a theoretical model of the U.S. economy and our economic methodology. We then proceed to test for links between finance and the real economy and present an estimate of this relationship.

2 General overview of the U.S. financial system

The strength of the expansion of the U.S. economy through the 1990s contributed to the fact that the U.S. financial system entered the previous recession (2001-2002) with an adequate level of capital. The relatively short duration of the recession also limited the severity of losses for financial institutions. Lin and Schimidt (2002) explain that the financial sector was the only private industry that continued to grow during the 2001-2002 recession. Effective monetary and fiscal policy in response to situation also played an important role in limiting the depth of the crisis by helping the recovery. Most U.S. states managed to weather this recession fairly well because their fiscal health was in good shape, allowing them to maintain constant nominal spending (Maag and Merriman, 2007).

With the new economic situation characterized by the serious effects of a very deep financial crisis, profound imbalances threaten economic prosperity again. Indeed, households in the U.S. mostly live on credit and do not hesitate to use any possible means of financing to maintain high consumption. The financial system has therefore seen a proliferation of innovations that transfer risks and increase the complexity of both financial and operational risk management. Changes in the structure of financing and the nature of the financial intermediation process have reinforced the importance of cooperation between supervisory authorities. The sources of potential risk for stability of the financial system are not limited to banks. Financial institutions increasingly operate in a grey area beyond the legal boundaries which define the responsibilities of the various financial authorities.

The seemingly simple structure of the U.S. financial system now often involves complex series of transactions intended to spread risks further. This increase in the number of transactions needing to be settled separately creates new risks that need to be managed. Thus, as pointed out by Biacabe (2008), the subprime crisis is a pathological form of a widespread practice. Households' preference for consumption rather than investment worsened the external account deficit which, combined with the public deficit, forms what is called twin deficits. This state of the

U.S. economy has contributed to greater external debt. Debt securities held by private foreign economic agents have been accumulating for some time. For example, the Bank of China alone has accumulated a balance of about $1,600 billion (Biacabe, 2008) . This situation can result in foreign funds taking control of U.S. companies. As an illustration of this situation, Elwell et al. (2007) cite the example of the Maytag Corporation, which was taken over on June 20, 2005 by the Haier Group, a large Chinese manufacturer of household appliances which bid $1.28 billion for the American company. The present economic challenges in the U.S. also contribute to the development of a national sentiment that the economic security of Americans should be protected. They also raise questions about of the feasibility of working towards national objectives such as stability, reducing unemployment and restoring equilibrium to the national accounts. Moreover, the rapid rate of the slowing of growth suggests that this is not a normal step in the United States' typical business cycle.

3 A Model of the U.S. Economy

In order to focus on the financial structure of the U.S. economy, we use the model developed by Williamson (1989). This model allows us to account for financial intermediation over the course of the U.S. business cycle. The banking sector's endogenous responses to disturbances in the real economy mean that it is important to include this relationship in models of the business cycle. In particular, it would clarify the relationship between production technologies and the intermediation process. In the theory we introduce here, cyclical variation can be interpreted as resulting from technological shocks which affect the costs of intermediation. The model is based on a microeconomic approach inspired by Sargent and Wallace's (1982) overlapping generations model. It is assumed that the economy is composed of two groups of agents: lenders and entrepreneurs. It is also assumed that there are N agents born in each generation p and that these agents live for two periods. Lenders receive an endowment of one indivisible unit of time at birth and maximize the following utility function

$$E_p = (\delta l_p - e_p - e_{p+1} + c_{p+1}), \tag{1}$$

where l_p represents leisure, δ is the cost of leisure, e_p is the amount of effort spent and c_p is consumption in the period. Lenders can use their single unit of time to produce a unit of consumer goods or to consume a unit of leisure. Entrepreneurs do not receive any endowment of time, consumer goods or effort in either of the periods of their life. In order to operate, an entrepreneur in generation p also has access to an investment project that requires K units of consumer goods as inputs. The project obtains a random yield of ϖ, for which $Pr[\varpi \preceq \omega] = H(\omega, \theta, \phi_p)$. ϕ_p is the common shock affecting all entrepreneurs' investment projects and θ is a parameter specific to each entrepreneur that determines the probability distribution. The project's returns are then independently assigned to entrepreneurs who can observe the returns on their own project ω. Every other agent, however, has to spend γ units of effort to observe ω. A financial institution who lends to an entrepreneur with parameter θ in period p has a probability of failure of $Pr[\omega \prec x_p(\theta)]$ where $x_p(\theta)$ is the promised payment per entrepreneur. The optimal arrangement occurs when the entrepreneur fulfills the promised payment if the return is ω such that $\omega \succeq x_p(\theta)$ whereas the intermediary is paid as much as ω if $\omega \prec x_p(\theta)$. Finally, the depositor's expected return has the form

$$\pi(x_p, \theta, \phi_p) = x_p - \int_0^{x_p} H(\omega, \theta, \phi_p) d\omega - \gamma H(x_p, \theta, \phi_p). \tag{2}$$

Let R_p be the expected return per unit of consumption goods that financial institutions invested in entrepreneurs' projects. Thus, for firms that meet the loan conditions[1], the promised payment

[1] These conditions are such that entrepreneurs receive funding if $\pi(x^*, \theta, \phi_p) \succeq R_p K$ where x^* is the level of x that maximizes π.

x_p is such that

$$\pi(x_p, \theta, \phi_p) = R_p K. \tag{3}$$

Let θ' be the value of θ in a diversified banking system[2] and $G(\theta)$ the number of agents who are entrepreneurs with $\theta \prec \theta'$. The number of banks that fail in period $p+1$ is then

$$\Psi_{p+1} = N \int_{\theta_p'}^{\bar{\theta}} H(x_p(\theta), \theta, \phi_p) g(\theta) d\theta, \tag{4}$$

where $g(\theta) \equiv DG(\theta)$. In order to analyze the sectoral co-fluctuations of the U.S. economy, we assume a state of static equilibrium where $\phi_p = \phi$ for all p. Thus, $R_1 = R_2$ and $\theta_1 = \theta_2$. Aggregate output Y_p includes output produced by lenders in period p and output produced by investment projects funded in period $p-1$

$$Y_p = Y_p^1 + Y_{p-1}^2. \tag{5}$$

Given that the shock ϕ_p is positively serially correlated, production in sectors receiving the highest quantity of credit is Y_{p-1}^2, which tends to be higher because investment in the previous period increases production. Aggregate output therefore becomes higher in these sectors. The probability of failure is higher for banks funding projects in sectors where entrepreneurs with the same θ face a higher promised payment, which occurs in sectors with riskier investment projects. In this context, we can reasonably suppose that the aggregate shocks affecting aggregate variables are similar for each sector and are directly related to common shocks observed in the financial sector. Indeed, changes in asset prices in a given market tend to spread to other asset markets due to investors' portfolio adjustments. Similarly, shocks relating to liquidity and asset quality cause fund managers to make adjustments. These effects are transmitted through adjustments relating to asset markets or financial institutions and are triggered by common shocks in various sectors of the real economy. In such a case, the aggregate variables share relatively large co-movements which can be econometrically modeled using a factor model, as presented in the next section.

4 Econometric approach

4.1 The econometric model

We consider that the variables have a factor structure and that the number of common factors is r. The data generating process is

$$y_{it} = F_t \lambda_i + e_{it}, \tag{6}$$

where $t = 1, \ldots, T$ and $i = 1, \ldots, N$. y_{it} is a vector of observations for the ith individual, F_t is a $(T \times r)$ matrix representing the factor process, λ_i is a $(r \times 1)$ vector of factor loadings and the $(T \times 1)$ vector e_{it} is the idiosyncratic term. We use principal component analysis to estimate the number of factors and the common factors. The matrix of estimated factors $\tilde{F}$ is equal to $\sqrt{T}$ multiplied by the eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix yy'/NT. Under the normalizations $\Lambda'\Lambda/N = I_r$ and $F'F/T = I_r$, the matrix of factor loadings can be obtained by ordinary least squares with $\tilde{\Lambda}' = (\tilde{F}'F)^{-1}\tilde{F}'y = \tilde{F}'y/T$. In order to estimate the number of common factors, we use the criterion[3] developped in Bai

[2] The authors also consider the restrictive case where banks are similar and offer the same types of services.

[3] Other criteria are developed by these authors, but BIC_3 criterion is more appropriate in this case, given the structure of our panel.

and Ng (2002) called BIC_3, which is an adaptation of the usual BIC criteria. Let F be a matrix of r factors and $V(r,F) = \min_{\Lambda} \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \lambda_i^{'}\tilde{F}_t)^2$ the sum of squared residuals (divided by NT) of the regression of y_{it} on the r factors for each i. To find r one can use[4] $BIC_3(r) = V(r,\tilde{F}) + r\hat{\sigma}^2(r_{max})\left(\frac{(N+T-r)\ln(NT)}{NT}\right)$.

4.2 Testing for links between estimated and observed factors

In this subsection, we present the $M(j)$ test (Bai and Ng, 2006) that can be used to test for links between the estimated macroeconomic factors and the observed financial factors. Let F_{jt}^o be an element of vector F_t^o representing the observed factors. The aim is to test if there is any δ_j such that $F_{jt}^o = \delta_j^{'}F_t$ for all t. It may initially seem intuitive to regress y_{it} on F_{jt}^o and then to assess the explanatory power of F_{jt}^o. If there is a significant relationship between F_t and F_{jt}^o then F_{jt}^o should be able to explain y_{it}. However, this procedure is not entirely satisfactory because, even though F_t^o is a proxy for F_t, the correlation between them would be very weak if the variance of e_{it} is large (Bai and Ng, 2006). In such a case, the explanatory power of this relationship may not be an appropriate criterion to test for links between macroeconomic and financial factors. Using $\hat{\gamma}_j$, the estimated value obtained for γ_j from the least squares regression $F_{jt}^o = \gamma_j^{'}\tilde{F}_t + \eta_{jt}$, Bai and Ng (2006) propose to define $\hat{F}_{jt}^o = \hat{\gamma}_j^{'}\tilde{F}_t$ and then to test the distance between the two curves $\hat{F}_{jt}^o$ and F_{jt}^o. The t-statistic they use is

$$\tau_t(j) = \frac{(\hat{F}_{jt}^o - F_{jt}^o)}{\left(var(\hat{F}_{jt}^o)\right)^{1/2}}. \tag{7}$$

$M(j)$ is obtained as follows

$$M(j) = max_{1 \preceq t \preceq T}\tau_t(j). \tag{8}$$

If there is no serial correlation in the idiosyncratic term, then under the null hypothesis[5] we have $F_{jt}^o = \delta^{'}F_t$. Note that, τ_{tj} has a standard normal limiting distribution. Let $Avar(\hat{F}_{jt}^o)$ denote the asymptotic variance[6] of $\sqrt{N}(F_{jt}^o - F_{jt})$, while the asymptotic variance divided by N has the form $var(\hat{F}_{jt}^o) = \frac{1}{N}Avar(\hat{F}_{jt}^o)$. Using the normalization of $\tilde{F}^{'}\tilde{F}/T$, we can define[7] $\hat{var}(\hat{F}_{jt}^o) = \frac{1}{N}\hat{\gamma}_j^{'}\tilde{V}^{-1}\tilde{\Gamma}_t\tilde{V}^{-1}\hat{\gamma}_j$. The construction of the variance is then based on $\tilde{\Gamma}_t$. Given that the e_{it} are orthogonal, we define $\tilde{\Gamma}_t = \frac{1}{N}\sum_{i=1}^{N}\tilde{e}_{it}^2\tilde{\lambda}_i\tilde{\lambda}_i^{'}$. It is then possible to construct $\hat{var}(\hat{F}_{jt}^o)$ and to test whether F_{jt}^o has links with the estimated factors using the critical values of $M(j)$.

4.3 Panel Unit Root Test

In order to test for unit roots, the econometric model is augmented with a heterogeneous deterministic trend D_{it} to get

$$y_{it} = D_{it} + \lambda_i^{'}F_t + e_{it}, \tag{9}$$

y_{it} is $I(1)$ if at least one of the factors is not stationary, if the idiosyncratic term is not stationary, or if neither are stationary. Of course, there is nothing *a priori* preventing differences in the orders of integration for F_t and e_{it}. Thus, instead of conducting unit root tests on y_{it}, both components are

4 $\hat{\sigma}^2$ is the estimator of $(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}E(e_{it})^2$, r_{max} is the maximum number of factors and we set $r_{max} = 6$ in the empirical section.

5 $N,T \longrightarrow \infty$ with $\sqrt{N}/T \longrightarrow 0$.

6 $Avar(F_{jt}^o) = plim\bar{\gamma}_j Avar(\tilde{F}_t)\bar{\gamma}_j = plim\bar{\gamma}_j\tilde{V}^{-1}\left(\frac{\tilde{F}F}{T}\right)\Gamma_t\left(\frac{\tilde{F}F}{T}\right)\tilde{V}^{-1}\bar{\gamma}_j$ and $\Gamma_t = \lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}E(\lambda_i\lambda_j^{'}e_{it}e_{it})$.

7 V is a $r \times r$ diagonal matrix consisting of the r largest eigenvalues of $y^{'}y/(NT)$ in decreasing order.

tested for non-stationarity. This procedure is called PANIC (Panel Analysis of Non-stationarity in the Idiosyncratic and Common components) and was developed by Bai and Ng (2004). The advantage of this method is that it allows us to specify whether the source of non-stationarity is general or specific. In our case, we are interested in the presence of a general source of non-stationarity, so we only look for the presence of unit roots among the common components. Two features may be considered to test for the presence of unit roots among the common factors.

– Model with a constant

$$y_{it} = c_i + \lambda_i^{'} F_t + e_{it}. \tag{10}$$

We consider two cases for conducting the unit root test on the common factors when there is a constant in the model. The first is the case of a single factor where it is possible to use a standard ADF test[8]

$$\Delta \tilde{F}_t = c + \beta_0 \tilde{F}_{t-1} + \beta_1 \Delta \tilde{F}_{t-1} + \, .. \, + \beta_h \Delta \tilde{F}_{t-h} + \nu_{it}. \tag{11}$$

In the other case, we have $r \succ 1$. In this situation, two statistical figures can be used, based on the r estimated factors $\tilde{F}_{m,t}$, for $m = 1 \, .. \, r$. The statistics are based on those proposed by Stock and Watson (1988) who aimed to test whether the real part of the smallest eigenvalue from the matrix of the autoregressive coefficients is equal to one. These two statistics, $MQ_c(m)$ and $MQ_f(m)$, require successive sequences of tests, much like the Johansen (1988) test for the number of cointegration vectors. The motivation for using the r common factors as a basis for these tests is that individually testing each factor for the presence of unit roots tends to overestimate the number of common stochastic trends, denoted as r_1.

– Model with a linear trend

$$y_{it} = c_i + \alpha_i t + \lambda_i^{'} F_t + e_{it}. \tag{12}$$

In this model, the unit root test applied to the factors can also distinguish the cases of $r = 1$ and $r \succ 1$. In the first case, we use an ADF model with a constant and a linear trend.

$$\Delta \tilde{F}_t = c_0 + c_1 t + \beta_0 \tilde{F}_{t-1} + \beta_1 \Delta \tilde{F}_{t-1} + \, .. \, + \beta_h \Delta \tilde{F}_{t-h} + \nu_{it}. \tag{13}$$

If $r \succ 1$, one can use the same approach as when the model has a constant. Next, it is assumed, as per Dufrenot et al. (2007) that the common factors follow an autoregressive process and that there is a cointegration relationship between the stochastic trends. It is then possible to identify a number of relationships between the factors in the long-run equilibrium. We use the Johansen (1988) trace test to test the hypothesis that there are a maximum of q cointegration vectors. The error correction model corresponding to this long-run relationship is as follows

$$\Delta F_t^o = \alpha_1 error_{t-1} + \sum_i \beta_i^{'} \Delta F_{t-i}^o + \sum_j \theta_j^{'} \Delta \tilde{F}_{t-j} + \xi_t, \tag{14}$$

where $error_t$ is the error correction term from the estimated cointegration relationship.

5 The data

This study uses annual data covering the years 1964-2008. They are classified into four categories[9] relating to output, employment, housing and a category which includes public expenditures, receipts and investment. The distinction between the different categories allows us to study the relationship between the changes in financial markets and the variation of the selected macroeconomic variables in these categories.

[8] where Δ denotes the first-difference operator.

[9] List of data series is available at http://www.u-bourgogne.fr/leg/z-outils/documents/docMCPichery.pdf

– Real output

The category of variables denoted as $OUTPUT$ allows us to explore the link between the disturbances observed in the production sectors and changes in U.S. financial markets. These data are all from the Federal Reserve Economic Data[10].

– Employment

To study the relationship between the factors in the U.S. housing and financial markets, a panel of 20 variables related to employment in the U.S. is also selected. These variables are from the U.S. Bureau of Labor Statistics[11] and this sample is called $EMPL$.

– Housings

Another panel of 20 variables, this time relating to the U.S. real estate market, are used to study the relationship between the common factors of the U.S. housing sector and those in financial markets. This set of variables is called $HOUSING$ and is from the U.S. Census Bureau database[12].

– Public receipts, expenditures and investment

This last category is called GOV and uses 20 data series from the Federal Reserve Bank of St. Louis[13]. These variables are diversified, including public receipts, expenditures and investments. The relationship between finance and the twin deficits in the U.S. are explored using this data.

The common factors that we consider to be responsible for fluctuations in financial markets in the United States are the three factors used by Fama and French (1993), respectively called $MARKET$, SMB and HML, and cover the years 1964-2008. Fama and French (1993) built their database using the weighted values of 6 portfolios. The $MARKET$ factor is the weighted return of the NYSE, AMEX, and NASDAQ minus the return on 1 month treasury bills as reported by Ibbotson Associates. SMB is the difference between the average return of three small portfolios and three large portfolios. Finally, HML is average return on two values and two growth portfolios.

6 Test for links between financial factors and macroeconomic factors

The purpose of this section is to test for links between the common factors underlying co-movements in financial markets and other factors which cause fluctuations in the real economy in the United States. The question is whether or not the three common factors that Fama and French (1993) identify as shocks affecting the stock market are the same common shocks that underlie co-movements in the real economy. To this end, we implement the $M(j)$ test (Bai and Ng, 2006) In applying this test, the variables are expressed in first difference to account for the possible presence of unit roots and then are normalized. In each case, we start by estimating the number of factors, denoted r, and the factors themselves using the procedure described in subsection 4.1.

[FIGURE 1 HERE]

The results of the $M(j)$ test can be found in Table 1. Relative to the $OUTPUT$ and GOV data series which respectively yield 5 and 6 common factors, the results show that the co-movements in the housing market ($r = 5$) and employment ($r = 6$) are much more sensitive to co-movements

[10] http://www.federalreserve.gov
[11] http://www.bls.gov
[12] http://www.census.gov
[13] http://research.stlouisfed.org

in the stock markets. Indeed, the test statistics have the lowest values in these two samples. Moreover, when considering the $MARKET$ factor, the hypothesis that common shocks which explain co-movements of stock returns are the same as the common shocks affecting co-movements in the housing market is verified by the $M(j)$ test at the 5% level[14]. In other words, the co-fluctuations in U.S. financial markets correspond exactly with the common shocks recorded in the housing market.

[TABLE 1 HERE]

As stressed by Whalen (2008), disturbances in the housing market lead to changes in investor preferences. In the case of negative shocks, complex assets structures such as those containing subprime mortgages are abandoned in favor of simpler assets. This may negatively affect stock returns. Figure 1 illustrates the relationship between $MARKET$ and common factors in the housing market.

7 Estimation of the relationship between financial and macroeconomic factorss in U.S.

In this section, we estimate relationships between financial and macroeconomic factors. We use the nonstationary panel data techniques presented in subsection 4.3 to explore this relationship. The unit root rests show that there are common stochastic trends among the four samples, reflecting the presence of factors which are integrated of order 1.

In terms of financial factors, individual unit root tests are applied using the generalized least squares Dickey-Fuller test proposed by Elliott et al. (1996), called DF-GLS. This test has advantages over the ADF test in terms of the statistical power of the test. Table 2 shows that only $MARKET$ has a unit root at the 5% level. The DF-GLS test rejects the hypothesis of nonstationarity for the SMB and HML factors. Note that different test models were considered when implementing the unit root tests. The results reported in Table 2 are the cases providing the best results as per the modified AIC criterion developed by Ng and Perron (2001). We also considered different test models for the unit root tests on macroeconomic common factors, this time using the Schwarz (1978) criterion to select the model.

[TABLE 2 HERE]

We use a similar approach to study the presence of cointegration relationships between data series. The presence of stochastic trends in the common factors for the real economy indicates that a cointegration relationship may exist. This leads to consideration of the possibility of spurious regressions, creating doubt about the validity of applying classical inference techniques.

Given that the $MARKET$ factor is the only financial factor which follows a unit-root process, we will only deal with this factor when investigating cointegration relationships. The high values resulting from the $M(j)$ test for $OUTPUT$ and GOV suggest that these series are not linked to financial markets. The estimated relationships between finance and the real economy will therefore deal with the employment market through the $MARKET-EMPL$ link and with the housing market through the $MARKET-HOUSING$ and $SMB-HOUSING$ links. Also, since $MARKET$ is the only one of the financial factors to have a unit root, the analysis of the cointegration relationship only deals with this financial factor. For both data series ($EMPL$ and $HOUSING$), the Johansen (1988) trace test detects the existence of cointegration relationships (see Table 3)

[14] The test statistic is equal to 2.88 and is less than the critical value of 3.28 at the 5% level

between their common factors. Common factors from the $EMPL$ sample have the largest number of cointegration vectors with $MARKET$. There are 5 cointegration relationships between these two sets of data, whereas the test shows only 1 cointegration vector between $HOUSING$ and $MARKET$.

[TABLE 3 HERE]

The presence of unit roots in our data series and the existence of cointegration between these roots imply a form of error correction representation. This provides an opportunity to determine the long-term relationships with financial factors, which are standardized and chosen as endogenous variables. Note that two data series are cointegrated if they are both non stationary and if it is also possible to find stationary linear combinations of these variables. The underlying idea is that cointegrated data series may evolve separately in the short term, but there are forces that cause them to move together over time. In other words, if the data series are cointegrated, there is a long term relationship similar to an equilibrium. Table 4 provides the results of the estimated long-run relationships.

[TABLE 4 HERE]

The presence of a long-run equilibrium is characterized by financial and macroeconomic factors tending to evolve in the same direction. Thus, any momentary movements away from the equilibrium are considered as random and temporary. The estimation of the error correction model presented in Table 5 show that the coefficient of the error correction term is negative and statistically significant for both the $EMPL$ and $HOUSING$ data series. This means that there is an error correction mechanism. Thus, there is general convergence between financial and macroeconomic factors. Indeed, financial markets regularly analyze a variety of macroeconomic informations and correspondingly adjust their anticipations. This is then reflected in the prices of shares, and the financial aggregates will tend to register the same co-movements as the real economy.

[TABLE 5 HERE]

Financial markets tend to adjust quite rapidly. This speed of adjustment is equal to 1 per year in the employment sector and is 0.98 per year for the housing market. Thus, for these two data series, adjustment to the long-run equilibrium is almost instantaneous. This corresponds with an average of 12 months for the employment market to fill its annual gap, whereas this period of time is 12.24 months for the real estate sector. In other words, shocks to the real estate market also affect American financial markets with an average delay of 0.24 months, or just 7 days. It can therefore be said that financial variables provide precise signals relating to changes in the real economy in the United States. Bellone et al. (2006) reach similar conclusions using the MS-VAR[15] model (Krolzig, 1997) which can anticipate the non-linear effects of macroeconomic variables by accounting for financial factors. They also stress that synchronization of co-movements between financial markets and the real economy was much larger before 1984 and that co-movements have become less persistent since then due to deregulation of financial markets that occurred in that year. Moreover, we also find that the relationships are much more significant in the long term than in the short run. For example, only F_4 from the labor market has a significant effect in the short term, whereas all the common factors have significant effects

[15] Markov-switching Vectorial AutoRegressive.

in the long-run. This can be explained by consumer behavior. If consumers expect disturbances (common shocks), and assuming that they are risk averse, they may try to protect themselves against a future decline in income by purchasing long term securities rather than short term ones. Such a case reflects a preference for guaranteed assets over securities with variable earnings, which will affect financial markets via changes in returns that it generates in the long term.

[TABLE 6 HERE]

Given that financial factor SMB is stationary, the $SMB - HOUSING$ relationship is studied using a classical OLS estimation. Table 6 shows the results of this estimation, which indicate a significant relationship between SMB and common factors in the housing market. This linkage is carried through F_1, F_2 and F_3, which all have significant effects. Finally, the estimated results for a finance-housing relationship also show that instability in the housing market has significant adverse effects on U.S. financial markets. All of the significant effects of common shocks in $HOUSING$ have a negative sign. This result can help us understand why the subprime shock had negative effects on banks, dealers, investors and the economy as a whole.

8 Conclusion

This study sought to explore the link between fluctuations in financial markets in the United States and the dynamics of the country's real economy. Our analysis starts with the assumption that shocks in U.S. financial markets are directly related to shocks in the real economy. We were able to highlight this link by focusing on econometric theory for non-stationary panel data.

The analysis shows that the factors have common stochastic trends for each data series considered and that it is therefore necessary to adopt strategies from the econometrics of non-stationary time series, including the theory of cointegration, to explore the links between financial and macroeconomic variables. This approach has led us to consider two types of relationships: a long-run relationship determined via cointegration equations and a short-term relationship specified using an error correction model.

The results of the estimations prove that there are significant links between the common shocks that affect the employment and housing markets, and those common shocks which underlie co-fluctuations in financial markets. These estimates also yield an error correction mechanism for each of the two sets of data. It is furthermore shown that U.S. financial markets adjust to a new equilibrium very quickly. This means that some forces must be in play, almost instantaneously pulling U.S. financial markets along with the real economy. Thus, it is clear from this study that the current situation faced by finance in the United States is most likely a reflection of the economic disturbances in employment and the real estate sector in this country.

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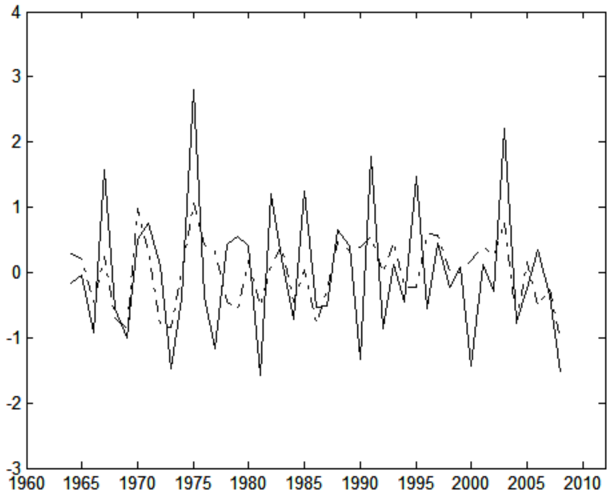

Fig. 1 Factor processes $MARKET - HOUSING$ *Solid line* : ΔF^{o}_{jt} *Dotted line* : $\hat{\gamma}_j'\Delta\tilde{F}_t$

Table 1 Results of the $M(j)$ test

	FINANCE		
Samples	*MARKET*	*SMB*	*HML*
OUTPUT T=45 N=20	19.11***	13.363***	24.914***
EMPL T=45 N=20	6.0727***	11.023***	7.4645***
HOUSING T=45 N=20	2.8839	4.2419***	11.395***
GOV T=45 N=20	8.9557***	13.977***	19.587***

Notes : The critical values at the 5% and 1% thresholds are respectively 3.283 and 3.775. (**), (***) denote rejection of the null hypothesis, respectively at the 5% and 1% thresholds. T is the time dimension and N the number of variables of interest.

Table 2 Results of the unit root tests

Samples	$\hat{r}$	$\hat{r}_1(MQ_c)$	$\hat{r}_1(MQ_f)$	$MQ_c(\hat{r}_1)$	$MQ_f(\hat{r}_1)$
OUTPUT T=45 N=20	5	5	5	-38.908	-19.431
EMPL T=45 N=20	6	6	6	-52.387	-48.216
HOUSING T=45 N=20	5	5	5	-16.894	-21.706
GOV T=45 N=20	6	6	6	-25.893	-34.569
DF-GLS tests on financial factors					
$MARKET$			-1.286		
SMB			-3.311**		
HML			-4.773***		

Notes : $\hat{r}$ is the number of common factors, r_1 the number of common stochastic trends and MQ the unit root statistics. ** (resp. ***) indicate rejection of the null hypothesis (unit root) at the 5% (resp. 1%) level. T is the time dimension and N the number of variables of interest.

Table 3 Johansen trace tests

	FINANCE-EMPL			**FINANCE-HOUSING**		
	$Vector = (MARKET, \tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6)$			$Vector = (MARKET, \tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5)$		
q	$trace-st.$	$crit.val.(5\%)$	$crit.val.(1\%)$	$trace-st.$	$crit.val.(5\%)$	$crit.val.(1\%)$
0	184.62**	109.99	119.80	103.48**	94.15	103.18
1	126.75**	82.49	90.45	63.81	68.52	76.07
2	75.65**	59.46	66.52	41.73	47.21	54.46
3	46.935**	39.89	45.58	24.10	29.68	35.65
4	27.60*	24.31	29.75	8.71	15.41	20.04
5	11.33	12.53	16.31	3.47	3.76	6.65

Notes: The number of cointegration relationships corresponds to the line where the statistic is below the critical value. (*) and (**) respectively denote significant at 5% and 1% levels.

Table 4 Estimation of the long term relationship between financial markets and the real economy in U.S.

Samples		$\tilde{F}_1$	$\tilde{F}_2$	$\tilde{F}_3$	$\tilde{F}_4$	$\tilde{F}_5$	$\tilde{F}_6$	$trend$
EMPL T=45; N=20								
	$MARKET$	0.59**	2.33**	2.71**	-1.56**	0.84**	-0.18**	
		(2.65)	(4.41)	(3.77)	(-4.70)	(4.56)	(-2.42)	
HOUSING T=45; N=20								
	$MARKET$	-0.84**	-0.26	0.66**	-0.31**	-0.88**		0.06**
		(-2.06)	(-0.88)	(2.44)	(-2.65)	(-3.76)		(2.78)

Notes: values in parentheses correspond to t-statistics; (**) denote significant at the 5% level. T is the time dimension and N the number of variables of interest.

Table 5 Estimation of the short term relationship between financial markets and the real economy in U.S.

Samples	$error$	$\Delta MARKET$ (-1)	ΔF_1 (-1)	ΔF_2 (-1)	ΔF_3 (-1)	ΔF_4 (-1)	ΔF_5 (-1)	ΔF_6 (-1)
EMPL								
T=45; N=20								
$\Delta(MARKET)$	-1.00**	0.04	0.67	0.58	0.35	-1.63**	0.21	-0.34
	(-3.67)	(0.21)	(0.68)	(0.61)	(0.38)	(-2.15)	(0.38)	(-1.38)
HOUSING								
T=45; N=20								
$\Delta(MARKET)$	-0.98**	0.04	-0.85	-0.56	-1.39**	0.45	-0.79**	
	(-3.80)	(0.20)	(-0.73)	(-0.56)	(-2.17)	(1.17)	(-2.61)	

Notes: The values in parentheses are the t-statistics. (**) denote statistically significant at the 5% level. $error$ is the error term from the estimated cointegration relationship. T is the time dimension and N the number of variables of interest. Δ denotes the first-difference operator.

Table 6 OLS estimation of the relationship $SMB - HOUSING$

	Ordinary Least Squares 1964-2008			
dep.: SMB				$R^2 = 0.43$
Obs: 45				$\bar{R}^2 = 0.34$
	Coefficients	St-error	t-statistics	Probabilities
$constant$	0.6806	0.3472	1.9601	0.0573
F_1	-1.8045	0.4712	-3.8298	0.0005
F_2	-1.2700	0.4027	-3.1535	0.0031
F_3	-0.6858	0.2344	-2.9257	0.0058
F_4	0.0785	0.1031	0.7606	0.4516
F_5	-0.0279	0.1432	-0.1950	0.8465
$trend$	-0.0441	0.0161	-2.7315	0.0095