Mikael Juselius – Moshe Kim – Staffan Ringbom

Do markup dynamics reflect fundamentals or changes in conduct?

EUROJÄRJESTELMÄ
EUROSYSTEMET

Bank of Finland Research
Discussion Papers
12 • 2009

Suomen Pankki
Bank of Finland
PO Box 160
FI-00101 HELSINKI
Finland
☎ +358 10 8311

http://www.bof.fi
E-mail: Research@bof.fi

Bank of Finland Research
Discussion Papers
12 • 2009

Mikael Juselius* – Moshe Kim** – Staffan Ringbom***

Do markup dynamics reflect fundamentals or changes in conduct?

* University of Helsinki RUSEG and Hanken School of Economics and HECER. E-mail: mikael.juselius@helsinki.fi. Corresponding author.
** Universitat Pompeu Fabra. E-mail: kim@econ.haifa.ac.il.
*** Hanken School of Economics and HECER. E-mail: staffan.ringbom@hanken.fi.

This paper was initiated when Moshe Kim was Distinguished Senior Fellow of Näringslivets Foundation at the Swedish School of Economics. He thanks Näringslivets Foundation and Jouko Vilmunen from the Research Unit at the Bank of Finland for their hospitality and support. Mikael Juselius thanks the Research Unit at the Bank of Finland for its hospitality and support. We thank Søren Johansen and Josef Molnar for their feedback on an earlier draft.

http://www.bof.fi

ISBN 978-952-462-506-7
ISSN 0785-3572
(print)

ISBN 978-952-462-507-4
ISSN 1456-6184
(online)

Helsinki 2009

Do markup dynamics reflect fundamentals or changes in conduct?

Bank of Finland Research
Discussion Papers 12/2009

Mikael Juselius – Moshe Kim – Staffan Ringbom
Monetary Policy and Research Department

Abstract

Persistent shifts in equilibria are likely to arise in oligopolistic markets and may be detrimental to the measurement of conduct, related markups and intensity of competition. We develop a cointegrated VAR (vector autoregression) based approach to detect long-run changes in conduct when data are difference stationary. Importantly, we separate the components in markups which are exclusively related to long-run changes in conduct from those explained solely by fundamentals. Our approach does not require estimation of markups and conduct directly, thereby avoiding complex problems in existing methodologies related to multiple and changing equilibria. Results from applying the model to US and five major European banking sectors indicate substantially different behavior of conventional raw markups and conduct-induced markups.

Keywords: markups, cointegration, VAR, macroeconomic fundamentals, competition, banking

JEL classification numbers: C32, C51, G20, L13, L16

Kuvastavatko hintamarginaalit talouden perustekijöiden vai kilpailukäyttäytymisen muutoksia?

Suomen Pankin keskustelualoitteita 12/2009

Mikael Juselius – Moshe Kim – Staffan Ringbom
Rahapolitiikka- ja tutkimusosasto

Tiivistelmä

Oligopolistisilla markkinoilla todennäköisesti esiintyy pysyviä tasapainomuutoksia, jotka vaikeuttavat kilpailukäyttäytymisen, marginaalin ja kilpailun mittaamista. Tässä tutkimuksessa kehitetään yhteisintegroituvaan vektoriautoregressiiviseen prosessiin perustuva menetelmä, jolla voidaan identifioida muutokset pitkän ajan kilpailukäyttäytymisessä, kun aikasarjat ovat differenssi-stationaarisia. Etenkin työssä erotellaan toisistaan ne marginaalin komponentit, jotka ovat seurausta kilpailukäyttäytymisen muutoksesta, ja ne, jotka ovat seurausta talouden taustatekijöistä. Lähestymistapa ei vaadi marginaalin eikä kilpailukäyttäytymisen suoranaista mittausta, joten näin vältytään niistä monimutkaisista menetelmällisistä ongelmista, jotka liittyvät useamman tasapainon tilanteisiin ja tasapainomuutoksiin. Menetelmää sovelletaan työssä Yhdysvaltain ja viiden suuren Euroopan maan pankkisektoreihin. Tutkimuksessa osoitetaan, että suorasti mitatun marginaalin kehitys ja pitkäaikaisen kilpailutasapainon kehitys eroavat toisistaan huomattavasti.

Avainsanat: hintamarginaali, yhteisintegroitunut VAR malli, kilpailu, talouden taustatekijät, pankkisektori

JEL-luokittelu: C32, C51, G20, L13, L16

Contents

1 Introduction

Measurement of the evolution of markups, market power and competition intensity are all pertinent to numerous core economic issues.[1] This paper offers an alternative novel approach to such measurement and applies it to the banking sector. The literature dealing with market power measurement has to a large extent been silent regarding unit-roots in prices, markups and fundamentals. This may impose severe limitation on the interpretation and usage of results pertaining to market power and competitive arrangements and their effect on core issues. In particular, if cointegration between markups and their possible 'determinants' cannot be verified, the estimated relationships may be spurious. Moreover, it is important to understand how and why markups change. To what extent are changes in markups conduct-dependent rather than fundamentals-dependent?[2] Increasing margins are traditionally taken to be indicative of excessive increase in market power or collusion when in fact they may often be explained by changes in exogenous fundamentals.[3] This issue can have important ramifications for microeconomic as well as macroeconomic policies which may benefit from the separation of these effects. It would be useless, for instance, to go after coordinated behavior if firms are just reacting non-cooperatively to changing fundamentals. This suggests that we should be more concerned with the extent to which changes in markups reflect dynamic changes in endogenous conduct than the extent to which they reflect direct autonomous effects of exogenous fundamentals. Further, it is useful to distinguish between short-run changes in conduct generated by various short-lived frictions and adjustments, which tend to gravitate toward some *stable long-run conduct* regime, and *changes in long-run conduct*, which are generated by transitions to new regimes. Viable public policy toward firms exhibiting increasing markups can be rather potent when directed at elements propagated by changes in long-run conduct rather than at those which are due to exogenous changes in the environment or those which are short lived.

In this paper, we offer an empirical approach for identifying changes in long-run conduct. We also decompose the markup into its conduct-related and fundamentals-related components.[4] We demonstrate that these components can be separated from each other by the moving average representation of a cointegrated VAR-model for prices and fundamentals. Successful separation can thus give rise to 'pure' conduct-related markups. The methodology we propose is novel in that it does not require the direct estimation of conduct and market power parameters thereby avoiding numerous and complex (measurement and conceptual) problems related to multiple and changing

[1] Drawing on microeconomic foundations, there has been a growing interest in the macroeconomic literature on the identification of imperfect competition at the sectoral level by estimating markups (Hall, 1988). Identifying markup behavior is important for the design of macroeconomic policies (Silvestre, 1993).

[2] Conduct refers to coordinated behavior or, more generally, the manner by which firms set their markups as reactions to changes in the perceived competitors behavior.

[3] We use markups and margins interchangeably throughout.

[4] Waterson (1984) demonstrates that price-cost margins may vary over time due to changes in industry demand elasticity (fundamentals) as well as due to changes in conjectural-variation (conduct).

equilibria. The proposed approach has additional advantages in that it, (*i*) utilizes the essential time series features inherent in the data, (*ii*) does not depend on the measurement of marginal costs, and (*iii*) does not require specification of the type of oligopolistic interactions that have produced the observed outcomes. The methodology is then brought to data from the financial intermediation sectors in the US and five major European countries. Results reported here are indicative of pronounced differences between the conventional 'raw' markups and those exclusively attributed to changes in conduct.

Our approach is based on the observation that changes in parameter regimes, conduct in our case, introduce non-linearities in the econometric equations and may cause the false impression of a unit-root in the residuals from linear estimates thereof (Leybourne et al, 1998; Nelson et al, 2001; Kilian and Taylor, 2003). Thus, changes in long-run conduct can be inferred from rejections of both linearity and (linear) cointegration between prices and a set of observed fundamentals.[5] Cointegration can be investigated, for example, by the cointegrated VAR methodology of Johansen (1996). If cointegration is not found, there is a stochastic trend in prices which is consistent with changes in long-run conduct, and which is orthogonal to the stochastic trends generated by the fundamentals. However, this stochastic trend may also be consistent with latent fundamentals. To safeguard against this possibility, the pricing equation error should be tested for the null hypothesis of linearity against the alternative hypothesis of non-linearities induced by regime shifts. A test of this hypothesis that is suitable for our framework has been developed by Choi and Saikkonen (2004). If linearity is rejected, the stochastic trend approximates the non-linear component of markups which exclusively pertain to changes in long-run conduct. Moreover, this stochastic trend can be separated from the components directly related to changes in the fundamentals by the moving average representation of a cointegrated VAR. It should be noted that this separation cannot be achieved in single equation frameworks, since it requires a representation of the stochastic trends generated by the fundamentals.

The remaining organization of the paper is as follows: Section 2 discusses related literature, and Section 3 presents the model. Section 4 presents the empirical decomposition. Section 5 brings the model to data from the financial intermediation sectors in the US and five major European countries, and Section 6 concludes.

2 Discussion and review of related literature

Several measures of market power have been suggested in the literature. A widely used measure for competition intensity and market power is the price-cost-margin. However, its theoretical foundations as a competition measure is not unidirectional regarding the relationship between markups

[5] Stationary effects of changes in short-run conduct are empirically indistinguishable from factors such as measurement errors. However, here we deal with the changes in long-run conduct only.

and competition, and neither are the emerging numerous empirical results.[6] Observed departures of price from marginal cost may not be solely indicative of imperfect competition or of the existence of market power (Domowitz, 1993; Domowitz et al, 1986) since margins may be affected simultaneously by both endogenous firm conduct and various exogenous fundamentals. Furthermore, conduct itself may be a function of supply, demand, institutional, and various other exogenous fundamentals. Other measures of market power range from theoretically motivated constructs such as the reciprocal of labor's share (Galí, 1994), various indexes of concentration such as the Herfindahl-Hirschman (HHI) index (relying on indirect inferences of market structure), direct estimates of markups based on cost functions (Lerner index), the Panzar and Rosse (1987) H-statistic, and recently the Boone (2008) measure of relative profit differences (RPD).[7]

Some of the empirical applications of existing models may require either the problematic specification of proxies for market power, such as the aforementioned measures, which may or may not correctly depict market power,[8] or require the estimation and testing of conduct parameters (Bresnahan, 1989 and Porter, 1983), which is problematic in an environment with changing conduct regimes.[9] A related and mostly overlooked problem in the aforementioned literature is that observed time series typically display stochastic trending which may be difficult to incorporate into existing approaches. For example, markup estimates require the estimation of non-linear cost functions, which is difficult to apply under difference stationarity. One solution is to take differences, but short-run responses and long-run responses can be completely different (economic theory usually pertains to the latter). Among other existing remedies are models utilizing cross section data or collapsing the time dimension by taking averages. The first is of questionable value if there are changes in equilibria, whereas the second is incorrect if data are difference stationary as moments are time dependent in such cases.

Many of the available, theoretical as well as empirical, models generate a host of different results regarding the type, nature (cyclicality) and severity of conduct depending on the type of equilibria and games specified as well as the fundamentals governing the economic environment. In some models results are propagated by current and future demand (Green and Porter, 1984; Rotemberg and Saloner, 1986; Domowitz et al, 1986; Rotemberg and Woodford, 1992), in other models it is capacity constraints (Staiger and Wolak, 1992) or the volatility of the discount factor (DaBó, 2007), all of which are indicative of

[6]Theoretical papers like Rosenthal (1980) and Stiglitz (1989) present models where more intense competition leads to higher price-cost margins.

[7]The recent Boone (2008) RPD measure has the advantage of being monotone in competition but its empirical implementation necessitates similar constructs to those required for the conventional price-cost margin measure, and is not applicable to sectoral level analysis as it requires firm-level data.

[8]Carbó et al (2008) document that the coefficient of determination between net interest margins (a widely used measure for markup in the banking sector) and the Lerner index, between the Lerner index and the return on assets (ROA), and between ROA and HHI index are only .46, .44, and .39, respectively, using average values across 14 European countries.

[9]Estimation of conduct parameters has been previously criticized by Corts (1999).

the importance of both fundamentals as well as conduct in the determination of markups, market power, and state of competition. Moreover, conduct itself may be a function of the various fundamentals (Domowitz et al, 1986). Many studies have examined the nature of markup fluctuations over the business cycle.[10] Firms may change their behavior during the business cycle by, for instance, colluding or rationing their outputs.[11]

Specific industry studies, such as those analyzing banking markets, have also recently realized the important interplay between firm's conduct and exogenous fundamentals in the determination of margins (Kashyap et al, 1993) as banking markets are known to be oligopolistic (Berger et al, 2004).[12] Demirgüç-Kunt, Laeven and Levine (2004) document the fact that the conventional positive relationship between concentration and markups (net interest margins) in banking markets deteriorates when controlling for exogenous factors such as regulatory restrictions and various macroeconomic factors.[13] Claessens and Laeven (2005) report that they do not control for all factors possibly affecting financial sector behavior and thus cannot eliminate the possibility that omitted variables drive some of their results. Angelini and Cetorelli (2003) document that the process of regulatory reform had a sizable pro-competitive impact on the Italian banking industry (measured by the Lerner index). However, they are careful to emphasize that excluded factors (latent fundamentals) might have had a role in shaping the banking environment and the observed pattern of their indicators of competitive conditions. The aforementioned observations all point to the existing relational complexity between conduct and fundamentals and thus the need to further explore the dynamic nature and interplay among these. Given that markup dynamics are the result of these two interrelated sources, it is apparent that one would want to filter out and separate the dynamics of fundamentals from the dynamics of conduct both of which comprise the conventional raw measured (total) markup-dynamics, thereby enabling the detection and assessment of margins which are exclusively related to either conduct or to fundamentals.

The measurement of conduct-related margins has been subject to continuous efforts among researchers developing structural models as well. Structural models of oligopolistic arrangements are based on three major 'primitives': (*i*) demand functions, (*ii*) supply/cost functions, and (*iii*) equilibrium configuration. The problems in specifying and dealing with each of these primitives are well known. Marginal costs data are generally unreliable and their (mis)measurement may have pronounced impact on the estimated

[10] Rotemberg and Saloner 1986), Rotemberg and Woodford (1992), Domowitz et al (1986), and Green and Porter (1984).

[11] Bresnahan (1987) and Porter (1983) document such behavior for the automobile and railroad sectors respectively.

[12] Berger et al (2004) provide a comprehensive and instructive summary as to the state of research pertaining to banking competition.

[13] Demirgüç-Kunt, Laeven and Levine (2004) control for some fundamentals in their regression but are silent regarding the interrelationship between markup and fundamentals.

market power.[14] Additionally, the parameters of marginal cost functions are sensitive to the particular equilibrium assumed. In turn, restricting attention to one particular equilibrium introduces extreme difficulties in the presence of multiple equilibria which imply no unique outcome.[15] When there is no unique parameter vector describing the relationship between markups and fundamentals both estimation and interpretation is difficult. Furthermore, it also impacts on the ongoing debates regarding pro or counter cyclicality of markups, since under changing conduct there may be no unique steady state markups, thereby making it virtually impossible to measure its cyclical component. The problem is further exacerbated in dynamic analyzes where a continuum of time varying equilibria takes place (see Pakes, 2008, for an extensive and thorough review).

The assumption of stable regimes in existing methods for detecting market power is needed in order to get complete structural estimates of markups and conduct. Consequently, testing for regime stability is prerequisite to employing such methods and developing a proper test for it is indeed one of the objectives of this paper. However, at a deeper level, dynamic changes in endogenous conduct may themselves be an important indicator of market power, since such changes are more likely to occur in non-competitive arrangements (Pakes, 2008). Hence, we also demonstrate how to measure the component in markups which is solely due to changes in long-run conduct. Transitions to periods characterized by weakened competitive (collusive) behavior can be inferred directly from the time-path of this measure.

3 Model

We use the following notation: matrices will be denoted by capital letters, vectors in lower case bold letters and scalars in lower case letters. A matrix R can be decomposed as $R = (R_{j1},\, R_{j\mathbf{2}})$ where R_{j1} denotes the first column, and $R_{j\mathbf{2}}$ the remaining columns. We also make use of the partition $R_{j1} = (R_{11},\, R'_{\mathbf{21}})'$, where R_{11} is the first element of column 1 and $R_{\mathbf{21}}$ are the remaining elements of column 1. The row spaces of R can be decomposed analogously. A vector $\boldsymbol{r}$ can be decomposed similarly as $\boldsymbol{r} = (r_1,\, \boldsymbol{r}'_{\mathbf{2}})'$. Finally, if R is $d \times l$, where $l < d$, and of full column rank, then $R_\perp$ denotes the $d \times (d-l)$ orthogonal complement to R, ie, $R'R_\perp = R'_\perp R = 0$.

To make the aforementioned discussion and various considerations concrete, consider an industry consisting of $J > 1$ firms engaged in markup pricing. Denoting $\boldsymbol{f}_t$, a q dimensional vector of supply and demand fundamentals, and $p_{j,t}$, the product price of firm $j \in J$. In a perfectly competitive environment, prices are determined by the impact on marginal costs from the changes in the fundamentals. We denote this impact by $\boldsymbol{\theta}_j$. Deviations from a perfectly

[14] Al-Najjar et al (2008) *eg*, show that firms may distort their relevant costs by incorporating irrelevant fixed and sunk costs in their pricing decisions. Oliver et al (2006) show that their (short-run) estimates of the Lerner index market power measurement is pronouncedly affected when marginal costs are risk-adjusted.

[15] Ciliberto and Tamer (2007) provide a model admitting multiple equilibria by imposing strong parametric restrictions.

competitive environment are expressed by $\mu_{j,t}$, representing the markup of firm j at time t. Thus, in logarithms, the reduced-form pricing function of each firm j is

$$p_{j,t} = \mu_{j,t} + \boldsymbol{\theta}_j' \boldsymbol{f}_t \tag{3.1}$$

and the vector of fundamentals $\boldsymbol{f}_t$ is assumed to satisfy the process

$$\boldsymbol{f}_t = M\boldsymbol{d}_t + (I - \Lambda(L))^{-1} \boldsymbol{\varepsilon}_t \tag{3.2}$$

where $M\boldsymbol{d}_t$ are deterministic terms, L is the lag operator, $\Lambda(z) = \sum_{i=1}^{k} \Lambda_i z^i$ is a k:th order matrix polynomial in z, and $\boldsymbol{\varepsilon}_t$ is vector white noise with mean zero and covariance matrix Σ. We assume that $I - \Lambda(z) = 0$ implies either $|z| > 1$ or $z = 1$, ie, that there can be real valued unit-roots in $\boldsymbol{f}_t$, but no complex unit-roots.[16] We also assume that $\boldsymbol{f}_t$ is at most $I(1)$.

In a perfectly competitive environment $\mu_{j,t} = 0$ and $\boldsymbol{\theta}_j = \boldsymbol{\theta}$, since economic rents are competed away and unproductive firms cannot survive in the long-run. However, in non-perfectly competitive environments, markups may be positive (or even negative during price wars) and firms may differ in their responses to changes in fundamentals, as captured by (3.1).

In non-perfectly competitive industries, $\mu_{j,t}$ may be different from zero and is generally a function of the fundamentals.[17] We refer to the form and parameters of this function as *firm conduct*, which is deduced from the firms optimal response functions (the mapping from a firm's perceived rivals actions into its optimal response given the state of the fundamentals). For a particular equilibrium outcome, conduct remains constant. We make the simplifying assumption that the markup is a linear function of the fundamentals within a particular equilibrium. In other words, in an equilibrium indexed by e we have

$$\mu_{j,t} = \boldsymbol{m}_j' \boldsymbol{d}_t + \boldsymbol{\eta}_{j,e}' \boldsymbol{f}_t \tag{3.3}$$

where $\boldsymbol{m}_j'$ and $\boldsymbol{\eta}_{j,e}$ capture conduct in equilibrium e, and $\boldsymbol{m}_j' \boldsymbol{d}_t$ is the deterministic markup.

However, in multiple equilibria environments, conduct may vary whenever transitions to new equilibria occur. Such transitions are increasingly likely to occur with the level of market power possessed by firms, as discussed by Pakes (2008). We allow for this possibility by specifying transition functions between a maximum of $\bar{e}$ different equilibria. Let $0 \leq R_{t,e} \doteq R_e(\boldsymbol{\psi}_t; \boldsymbol{\kappa}) \leq 1$ be the general from of the transition function for equilibria e satisfying $\sum_{e=1}^{\bar{e}} R_{t,e} = 1$, where the transition variable $\boldsymbol{\psi}_t = \boldsymbol{\psi}(\boldsymbol{f}_t)$ is a continuous real valued vector function of the fundamentals (of dimension less or equal to q), $\boldsymbol{\kappa}$ contains $\bar{e} - 1$ threshold parameter vectors and $\bar{e}$ speed of adjustment parameter vectors. The $R_{t,e}$ can be interpreted as the weights given to each equilibrium during a transition depending on the location of $\boldsymbol{\psi}_t$ relative to

[16] Strictly speaking, the polynomial inverse in (3.2) does not exist as such when $I - \Lambda(1) = 0$. In this case we view the inverse as given by the Johansen-Granger representation theorem (Johansen, 1996). Including this technicality here would only complicate the notation without adding to the discussion. We reconsider this point in Section 4.

[17] This insight is advocated in the literature on endogenous markups pioneered by Hall (1988), Rotemberg and Woodford (1991), and Galí (1994), among others.

the threshold parameters. In the special cases when $\bar{e} = 1$, there is only one equilibrium and prices are linear functions of the fundamentals. This case is more likely to arise in highly competitive markets (it also arises when $J = 1$, ie, the monopoly case). An example of an empirically viable specification that follows this general transition structure is the smooth transition regression (STR) model for difference stationary variables by Saikkonen and Choi (204).[18] Multiplying (3.3) by $\sum_{e=1}^{\bar{e}} R_{t,e}$ produces

$$\mu_{j,t} = \boldsymbol{m}_j' \boldsymbol{d}_t + \sum_{e=1}^{\bar{e}} R_{t,e} \boldsymbol{\eta}_{j,e}' \boldsymbol{f}_t \tag{3.4}$$

and substituting (3.4) into (3.1) yields

$$p_{j,t} = \boldsymbol{m}_j' \boldsymbol{d}_t + \sum_{e=1}^{\bar{e}} \left(R_{t,e} \boldsymbol{\eta}_{j,e}' + \boldsymbol{\theta}_j' \right) \boldsymbol{f}_t \tag{3.5}$$

Up to this point we have deliberately kept the discussion of the transition dynamics at a general level. The reason is that we typically have very little information about the number of equilibria, $\bar{e}$, and the nature of transition between them. However, one of the innovations in this paper is that even without this information we can still *test* for the presence of changes in conduct in a straightforward manner. In addition, we can also separate that part of markups (and prices) that exclusively pertains to changes in conduct from that which directly pertains to changes in fundamentals.

The idea is to compare the general pricing function (3.5) with the special case obtained when there is only one equilibrium. When $\bar{e} = 1$, (3.5) is reduced to linear function

$$\tilde{p}_{j,t} = \boldsymbol{m}_j' \boldsymbol{d}_t + \boldsymbol{\zeta}_j' \boldsymbol{f}_t \tag{3.6}$$

where $\tilde{p}_{j,t}$ denotes the price conditional on $\bar{e} = 1$, $\boldsymbol{\zeta}_j = \left(\boldsymbol{\eta}_j + \boldsymbol{\theta}_j \right)$, and $\boldsymbol{\eta}_j$ denotes the conduct response to the fundamentals in the single equilibrium. Let $\delta_{j,t}$ denote the error from using (3.6) instead of (3.5). The expression for this error is

$$\delta_{j,t} = p_{j,t} - \tilde{p}_{j,t} = \sum_{e=1}^{\bar{e}} \left(R_{t,e} \boldsymbol{\eta}_{j,e}' - \boldsymbol{\eta}_j' \right) \boldsymbol{f}_t \tag{3.7}$$

and can be interpreted as a measure of the departure from linearity caused by the transitions between equilibria or, in terms of our economic setup, as a measure of the total effect on markups from changes in conduct. Note that when $\bar{e} = 1$, $\delta_{j,t} = 0$. However, when $\bar{e} > 1$, $\delta_{j,t}$ may be small or

[18] Related specifications are a variety of non-linear error correction models that allow for difference stationarity, for example threshold models (Balke and Fomby, 1997; Hansen and Seo, 2002), smooth transition models (reviewed in van Dijk et al, 2002), and Markov switching models (Camacho, 2005), among others. However, these specifications are not ideal for our purposes since they typically restrict regime transitions to the equilibrium adjustment coefficients and the short-run parameters, whereas cointegration relationships are assumed fixed.

large depending on the severity of the non-linearities caused by the transition dynamics. In practice, ignoring this type of transition dynamics may even induce the appearance of a unit-root in $\delta_{j,t}$ as is documented by Leybourne et al (1998) and Nelson et al (2001), among others. The intuition for this result is straightforward. If the departures in $\boldsymbol{\eta}_{j,e}$ from some mean level $\boldsymbol{\eta}_j$ tend to be small and short lived, $\delta_{j,t}$ will likely behave as a stationary serially correlated series. On the other hand, if the differences between the different $\boldsymbol{\eta}_{j,e}$ are large and long lived, the associated shifts in $p_{j,t}$ will have the appearance of a unit-root. Here, we refer to the first case as *stable long-run conduct* and to the second case as *changing long-run conduct.* Thus, if a linear pricing function is estimated it will take the form

$$p_{j,t} = \boldsymbol{m}_j' \boldsymbol{d}_t + \boldsymbol{\zeta}_j' \boldsymbol{f}_t + s_{j,t} \tag{3.8}$$

where

$$s_{j,t} = (1 - \lambda_j(L))^{-1} \nu_t$$

for some k:th order scalar polynomial $\lambda_j(z) = \sum_{i=1}^{k} \lambda_{j,i} z^i$ and the difference between the theoretical error $\delta_{j,t}$ and the empirical residual $s_{j,t}$ is independent with noise, i.e., $\delta_{j,t} - s_{j,t} = \xi_{j,t}$ capturing measurement errors.[19] The empirical transition shock ν_t is *uncorrelated but not independent* of $\boldsymbol{\varepsilon}_t$ by construction (provided that a constant is used in the regression) and has mean zero and variance σ_j^2. We assume that $1 - \lambda_j(z) = 0$ implies either $|z| > 1$ or $z = 1$ allowing for unit-roots in $s_{j,t}$. If $s_{j,t}$ contains a unit-root, prices and fundamentals will not be linearly cointegrated and the estimates of $\boldsymbol{\zeta}_j$ may be spurious. On the other hand, if $s_{j,t}$ is stationary, prices and fundamentals are either stationary as well, or linearly cointegrated with cointegration vector $\left(1, \boldsymbol{\zeta}_j'\right)'$ when $\boldsymbol{f}_t \sim I(1)$. Note that ν_t is assumed to be identical among firms which implies that if $s_{j,t} \sim I(1)$, then the stochastic trend is common to all firms, whereas the short-run dynamics in $s_{j,t}$ are allowed to differ since $\lambda_j(z)$ depends on firm's index. Without this assumption price differences between two firms could be infinitely large in the long-run, a feature inconsistent with the notion of firms belonging to the same market (Forni, 2004). Thus, $s_{j,t} = s_t^C + s_{j,t}^{C*}$ by the Granger representation theorem, where s_t^C is the approximate stochastic trend due the changes in long-run conduct and $s_{j,t}^{C*}$ is firms specific stationary component of $s_{j,t}$.

It is instructive at this point to relate our approach, which measures changes in long-run conduct, to the more conventional approaches that try to determine the level and nature of competition by estimating markups and their determinants. In terms of our setup, the goal of these approaches is evidently to estimate $\boldsymbol{\eta}_j$. This clearly requires a correct estimate of the markup μ_j since otherwise $\boldsymbol{\eta}_j$ is likely to be confused with $\boldsymbol{\zeta}_j = \boldsymbol{\eta}_j + \boldsymbol{\theta}_j$, which can be seen by comparing (3.6) with (3.3). As discussed earlier, measuring markups are riddled with difficulties and typically require strong assumptions on the industry structure as well as stable conduct. The problem becomes even more acute when there are changes in conduct since in that case $\boldsymbol{\eta}_{j,e}$,

[19] Having k equal in the lag polynomials of $\boldsymbol{f}_t$ and $s_{j,t}$ is not restrictive. Simply let k be the maximum of the number of non-zero lags appearing in both equation.

$e = 1, ..., \bar{e}$, must be estimated rather than $\boldsymbol{\eta}_j$ *even if* markups were correctly calculated. This requires knowledge on the number of equilibria and the nature of transition between them, which is unlikely to be available to the investigator. In contrast, our approach avoids these difficulties by restricting attention to markup variations which are due to variation in conduct itself.

So far, an implicit assumption in the discussion has been that all possible observations on $\boldsymbol{f}_t$ are available. This is rarely the case in practice and as a consequence the empirical error $\xi_{j,t} = \delta_{j,t} - s_{j,t}$ may contain some information related to latent fundamentals.[20] This does not cause problems for detecting long-run changes in conduct as long as $\xi_{j,t} \sim I(0)$, ie, as long as the *new* information (orthogonal to the observed fundamentals) contributed by the latent variables is stationary, since the stochastic trend in $s_{j,t}$ still reflects $\delta_{j,t}$ in that case. It can be argued that $\xi_{j,t} \sim I(0)$ is more likely when a 'large' set of observed fundamentals is used in the estimation. The reason is that only few common stochastic trends are typically found to underlie the long-run variation of fundamentals (Bai, 2004). This implies that it is sufficient for our purposes to use a set of fundamentals which is capable of representing these common trends, whereas additional fundamentals are strictly not required. Thus, the problem with latent fundamentals may be alleviated by using a large set of fundamentals. However, the non-linear nature of $\delta_{j,t}$ offers, at least in principle, a formal way of testing if $\xi_{j,t} \sim I(1)$, ie, if latent fundamentals are a cause for $s_{j,t} \sim I(1)$. In particular, we estimate a STR-model specification for the pricing equation (3.5) using the techniques developed by Saikkonen and Choi (2004) and test if the obtained residuals are stationary.[21] If stationarity is not rejected, we apply the linearity test in Choi and Saikkonen (2004). If the null hypothesis of linearity is rejected, we have verified that STR type of non-linearities were indeed significant and the cause of rejection of linear cointegration, ie, $\xi_{j,t} \sim I(0)$. However, if it is impossible to find a cointegrated STR model or if linearity is not rejected, we must conclude that latent fundamentals are the likely cause of $s_{j,t} \sim I(1)$.

Finally, we note that the arguments are invariant to (linear) aggregation up to the industry level. The reason is that s_t^C does not depend on the firm index due to the market definition and is therefore preserved under aggregation. For instance, aggregating (3.8) over the J firms by taking the arithmetic mean yields

$$p_t = \boldsymbol{m}'\boldsymbol{d}_t + \boldsymbol{\zeta}'\boldsymbol{f}_t + s_t \tag{3.9}$$

where $p_t = \frac{1}{J}\sum_{j=1}^{J} p_{j,t}$, $\boldsymbol{m} = \frac{1}{J}\sum_{j=1}^{J} \boldsymbol{m}_j$, $\boldsymbol{\zeta} = \frac{1}{J}\sum_{j=1}^{J} \boldsymbol{\zeta}_j$, and $s_t = s_t^C + \frac{1}{J}\sum_{j=1}^{J} s_{j,t}^{C*} \doteq (1-\lambda(L))^{-1}\nu_t$. In our empirical application we restrict attention to aggregate credit spreads in the financial intermediation sector.

Summarizing, non-linearities implied by changes in long-run conduct may cause the false impression of a unit-root in the residuals from a linear regression

[20]In addition, $\xi_{j,t}$ may also reflect stationary measurement errors, but such errors do not distort an approximate stochastic trend in $s_{j,t}$ (Hassler and Kuzin, 2008).

[21]Since there is considerable uncertainty with respect to the correct specification of the transition dynamics and number of regimes we refrain from interpreting the STR estimates. Here, we are merely concerned with establishing the cause for the appearance of the unit-root in $s_{j,t}$.

of prices on a set of observed fundamentals. Thus, *stable* long-run conduct can be inferred from finding linear cointegration between these variables. If linear cointegration is not found, however, we can distinguish between a 'false' unit-root caused, by changes in long-run conduct, and a 'real' unit-root, due to latent fundamentals, by testing for linearity against non-linear regime-shift dynamics. The components in markups that exclusively pertain to changes in long-run conduct can be separated from those components which are due to exogenous changes in the environment by the moving average representation of a cointegrated VAR-model for prices and fundamentals.

4 Empirical decomposition

In this section we demonstrate how to test prices for the presence of a stochastic trend which is orthogonal to the fundamentals. We also show how such a stochastic trend can be extracted from a cointegrated VAR-model. We restrict attention to the price aggregate (3.9) in the rest of this section.

In order to relate (3.9) to an empirical reduced form VAR, we derive the VAR representation of the $q+1$ dimensional vector $\boldsymbol{x}_t = (p_t, \boldsymbol{f}'_t)'$. This can be achieved by substituting (3.2) and the expression for s_t into (3.9). This yields

$$
\begin{aligned}
p_t &= \boldsymbol{m}'\boldsymbol{d}_t + \boldsymbol{\zeta}'\boldsymbol{f}_t + s_t \\
&= \boldsymbol{m}'\boldsymbol{d}_t + \boldsymbol{\zeta}'\boldsymbol{f}_t + (1-\lambda(L))^{-1}\nu_t \\
&\Longleftrightarrow \\
p_t &= \lambda(L)p_t + (1-\lambda(L))\,\boldsymbol{m}'\boldsymbol{d}_t + (1-\lambda(L))\,\boldsymbol{\zeta}'\boldsymbol{f}_t + \nu_t \\
&= \lambda(L)p_t + (\boldsymbol{\zeta}'\Lambda(L) - \lambda(L)\boldsymbol{\zeta}')\,\boldsymbol{f}_t + \nu_t + \boldsymbol{\zeta}'\boldsymbol{\varepsilon}_t \\
&\quad + (1-\lambda(L))\,\boldsymbol{m}'\boldsymbol{d}_t + \boldsymbol{\zeta}'\,(I-\Lambda(L))\,M\boldsymbol{d}_t
\end{aligned} \tag{4.1}
$$

where contemporaneous $\boldsymbol{f}_t$:s are eliminated in the last step. Combining (4.1) with (3.2) produce the desired reduced form VAR representation

$$
\begin{aligned}
\begin{pmatrix} p_t \\ \boldsymbol{f}_t \end{pmatrix} &= \begin{pmatrix} \lambda(L) & \boldsymbol{\zeta}'\Lambda(L) - \lambda(L)\boldsymbol{\zeta}' \\ \mathbf{0} & \Lambda(L) \end{pmatrix} \begin{pmatrix} p_t \\ \boldsymbol{f}_t \end{pmatrix} \\
&+ \begin{pmatrix} 1 & \boldsymbol{\zeta}' \\ \mathbf{0} & I \end{pmatrix} \begin{pmatrix} (1-\lambda(L))\,\boldsymbol{m}' \\ (I-\Lambda(L))\,M \end{pmatrix} \boldsymbol{d}_t \\
&+ \begin{pmatrix} 1 & \boldsymbol{\zeta}' \\ \mathbf{0} & I \end{pmatrix} \begin{pmatrix} \nu_t \\ \boldsymbol{\varepsilon}_t \end{pmatrix}
\end{aligned} \tag{4.2}
$$

which forms the basis of our empirical investigation. Note that the fundamentals enter prices dynamically due to the unobserved time varying markup. However, this poses no problem if ν_t can be recovered from (4.2) since $\lambda(L)$ is recovered from the lag polynomial of p_t.

The empirical counterpart of (4.2) can be written compactly as

$$
\boldsymbol{x}_t = \sum_{i=1}^{k} A_i \boldsymbol{x}_{t-i} + \Phi \boldsymbol{d}_t^{\Phi} + \boldsymbol{v}_t \tag{4.3}
$$

where the l dimensional vector $\boldsymbol{d}_t^{\Phi}$ and the $q \times l$ matrix Φ collects the *deterministic drift*,[22] and

$$\boldsymbol{\upsilon}_t = \begin{pmatrix} 1 & \boldsymbol{\zeta}' \\ \mathbf{0} & I \end{pmatrix} \begin{pmatrix} \nu_t \\ \boldsymbol{\varepsilon}_t \end{pmatrix} \doteq \Omega \boldsymbol{\varepsilon}_t^{\boldsymbol{x}} \tag{4.4}$$

collects the VAR residuals. When $\boldsymbol{x}_t \sim I(1)$ it is convenient to rewrite (4.3) in its corresponding error correction form

$$\Delta \boldsymbol{x}_t = \Pi \boldsymbol{x}_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta \boldsymbol{x}_{t-i} + \Phi \boldsymbol{d}_t^{\Phi} + \boldsymbol{\upsilon}_t \tag{4.5}$$

where $\Pi = \sum_{i=1}^{k} A_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{k} A_j$. For future use we define $\Gamma = I - \sum_{i=1}^{k-1} \Gamma_i$.

Cointegration can be tested as a reduced rank hypothesis on the Π matrix. If the rank, r, of Π is equal to $q+1$, then $\boldsymbol{x}_t$ is stationary, ie, $\boldsymbol{x}_t \sim I(0)$. If $0 < r < q+1$, then $\boldsymbol{x}_t \sim I(1)$ is cointegrated with r cointegration vectors and $q+1-r$ common trends. In this case

$$\Pi = \alpha \beta'$$

where α and β are two $((q+1) \times r)$ matrices of full column rank. If $r = 0$ then $\boldsymbol{x}_t \sim I(1)$ and the process is not cointegrated. When $\boldsymbol{x}_t$ is cointegrated, we also assume that $|\alpha'_{\perp} \Gamma \beta_{\perp}| \neq 0$ which ensures that $\boldsymbol{x}_t$ is not integrated of higher order than one (Johansen, 1996, theorem 4.2).

The significance of s_t^C can be indirectly tested by testing p_t for long-run exclusion, ie, testing (the liner restriction) that the first row of β is zero. In general, linear hypotheses on β can be tested in the form

$$\mathcal{H}_{\beta} : \beta = (H_1 \varphi_1, ..., H_r \varphi_r) \tag{4.6}$$

where $H_i((q+1) \times (q+1-m_i))$ imposes m_i restrictions on β_i, and $\varphi_i((q+1-m_i) \times 1)$ consists of $q+1-m_i$ freely varying parameters. The likelihood ratio test statistic of the hypotheses is asymptotically chi-square distributed. Thus, long-run exclusion of p_t can be tested by setting $H_i = (\mathbf{0}, I_{r-1})'$ for all i and the test is asymptotically distributed as $\chi^2(r)$.

Alternatively, the significance of s_t^C can also be tested directly from the moving average representation of (4.5). This is more appealing since we are also interested in measuring this stochastic trend. The moving average representation of (4.5) is given by

$$\boldsymbol{x}_t = C \sum_{i=0}^{t-1} \left(\boldsymbol{\upsilon}_{t-i} + \Phi \boldsymbol{d}_{t-i}^{\Phi} \right) + \sum_{i=0}^{t-1} C_i^* \left(\boldsymbol{\upsilon}_{t-i} + \Phi \boldsymbol{d}_{t-i}^{\Phi} \right) + \tilde{\boldsymbol{x}}_0 \tag{4.7}$$

[22] The term *deterministic drift* refers to the estimated deterministic components in (4.3), whereas the 'true' deterministic components of the process are referred to as the *deterministic trend*. For example, the deterministic trend of $\boldsymbol{x}_t$ is $M^{\boldsymbol{x}} \boldsymbol{d}_t = (\boldsymbol{m}, M')' \boldsymbol{d}_t$. Note that $\boldsymbol{d}_t$ in (4.2) is not in general equal to $\boldsymbol{d}_t^{\Phi}$ in (4.3), because $\boldsymbol{d}_t^{\Phi}$ is a function of current and lagged $\boldsymbol{d}_t$. See Johansen (1996) and Juselius (2006) for detailed discussions of the deterministic terms in the VAR model.

where $C = \beta_\perp(\alpha'_\perp\Gamma\beta_\perp)^{-1}\alpha'_\perp$, $\tilde{\boldsymbol{x}}_0$ collects the initial condition, and the zeros of the matrix polynomial $C^*(z) = \sum_{i=0}^{\infty} C_i^* z^i$ are outside the unit circle. The first right hand side term of (4.7) collects the stochastic trends with corresponding deterministic trends. The residual $\boldsymbol{\varepsilon}_t^{\boldsymbol{x}}$ can be recovered from (4.5) by pre-multiplying $\boldsymbol{v}_t$ by Ω^{-1}, where Ω is the Cholesky decomposition of the covariance matrix of $\boldsymbol{v}_t$ normalized to have ones in the diagonal. The Cholesky decomposition defines a particular choice of causal ordering of $\boldsymbol{x}_t = (p_t, \boldsymbol{f}'_t)'$. This is often problematic since different causal orderings gives different representations of $\boldsymbol{\varepsilon}_t^{\boldsymbol{x}}$. However, for our purposes p_t should be ordered at the end of the causal chain since ν_t is by definition the residual in prices that is orthogonal to the fundamentals, whereas the internal ordering of $\boldsymbol{f}_t$ is arbitrary.[23]

Using $\boldsymbol{v}_t = \Omega\Omega^{-1}\boldsymbol{v}_t = \Omega\boldsymbol{\varepsilon}_t^{\boldsymbol{x}}$ and $\nu_t = \Omega_{1j}^{-1}\boldsymbol{v}_t$, we see that ν_t is transmitted into $\boldsymbol{x}_t$ through Ω_{j1}. But by construction $\Omega_{j1} = (1, \boldsymbol{0}')'$, so we get

$$s_t^C = C_{1j}\Omega_{j1}\sum_{i=0}^{t-1}\Omega_{1j}^{-1}\boldsymbol{v}_{t-i} = C_{11}\sum_{i=0}^{t-1}\Omega_{1j}^{-1}\boldsymbol{v}_{t-i} \tag{4.8}$$

The significance of s_t^C is thus determined by the significance of the element C_{11}. The test statistic for this hypothesis is derived by Paruolo (1997).

By construction, the estimate of s_t^C starts and ends at the origin, since the VAR residual sums to zero. However, it may be of considerable interest to know if changes in conduct have increased or decreased markups over time. To this end, the corresponding deterministic counterpart of s_t^C must be derived. Let $\boldsymbol{m}'\boldsymbol{d}_t = \boldsymbol{m}^{C'}\boldsymbol{d}_t + \boldsymbol{m}^{C^*}\boldsymbol{d}_t$ be a decomposition of the deterministic markup analogous to the decomposition of s_t. We show (Appendix A) that the deterministic trend is given by[24]

$$\boldsymbol{m}^{C'}\boldsymbol{d}_t = C_{11}\sum_{i=0}^{t-1}\Omega_{1j}^{-1}\Phi^C\boldsymbol{d}_{t-i}^{\Phi} \tag{4.9}$$

where $\Phi^C = \alpha_\perp(\alpha'_\perp\alpha_\perp)^{-1}\alpha'_\perp\Phi$. Unfortunately, the constant in $\boldsymbol{m}^{C'}\boldsymbol{d}_t$ cannot be determined for reasons explained in the appendix. Thus, the best we can obtain is a measure of the development of $s_t^C + \boldsymbol{m}^{C'}\boldsymbol{d}_t$ from any initial point.

5 Empirical application

In this section we illustrate our approach for detecting changes in firm conduct in an application to the financial intermediation sector. We begin by discussing the particular empirical aspects related to financial intermediation.

[23] By contrast, if we were interested in obtaining the effects of shocks to the fundamentals, $\boldsymbol{\varepsilon}_t$, on the price, p_t, the causal ordering of $\boldsymbol{x}_t$ would be important.

[24] For completeness, Appendix A gives the full decomposition of s_t and $\boldsymbol{m}'\boldsymbol{d}_t$.

5.1 Financial intermediation

Determinants of credit spreads have been extensively studied in the literature.[25] A framework for analyzing credit spreads was provided in a seminal paper by Saunders (1981). In this framework, banking is viewed as a trading activity and therefore credit spreads are explained by the various risks associated with borrowing and lending. However, the Ho and Saunders framework ignores important costs in banking operations, such as labor[26] and capital costs, and does not model the dynamic nature of competition between banks explicitly.[27] For these reasons a wide variety of factors such as bank specific characteristics, market structure, institutional indicators, as well as some macroeconomic conditions are typically appended to explain credit spreads in cross-sectional or panel-data applications such as in Saunders and Schumacher (2000), Claessens et al (2001), Angelini and Cetorelli (2003), Demirgüç-Kunt, Laeven and Levine (2004) and Laeven and Majnoni (2005), among others.

In line with the Ho and Sounders framework we concentrate on the role of banks as financial intermediaries. Bank j sets its lending and deposit rates as a margin relative to the money market interest rate, ie, $r_{j,t}^d = r_t - a_{j,t}$ and $r_{j,t}^l = r_t + b_{j,t}$, where $r_{j,t}^d$ and $r_{j,t}^d$ are the deposit and lending rates respectively, r_t is the money market rate, and the margins are given by $a_{j,t}$ and $b_{j,t}$. The margins $a_{j,t}$ and $b_{j,t}$ reflect different types of risk and costs associated with financial intermediation, and in addition, possibly market power. In particular, depending on whether the bank faces excess demand for loans or excess supply of deposits, the bank is subjected to either *refinancing risk* or *reinvestment risk* as it must obtain or invest funds in the money market to cover its net liquidity position (Saunders and Schumacher, 2000). The bank is also subjected to *credit risk* as the realized return on loans is uncertain. These risks can be decomposed into market risk and bank specific idiosyncratic risk which is endogenous to the banks' decision problem. In addition to risk, there are also costs associated with financial intermediation such as labor and capital costs. Moreover, if banks have some degree of market power, they may increase margins by some 'pure' markup, which may as well be influenced by exogenous fundamentals, as is discussed in Section 3.

Summarizing, the price of the financial service provided by bank j is given by the credit spread, $p_{j,t} = a_{j,t} + b_{j,t}$, which is a function of; (i) the (expected) behavior of other banks, (ii) other endogenous decision variables, such as the bank specific risk profile, and (iii) a set of fundamentals that are exogenous to the bank, including market wide risk. The reduced form pricing rules of the

[25] Spreads are the ex-ante difference between loan and deposit interest rates, while margins are the ex-post rates. The main difference between spreads and margins are charge-off rates. These are controlled for in the present study by the business cycle measures that we use to capture economy wide risk and which are verified (Section 5.2) to explain long-run variation in charge-off rates and delinquency rates.

[26] In virtually all studies of banking costs, the share of labor amounts to at least 70% of total costs (not including funding).

[27] Ho and Saunders (1981) assume that banks have some degree of market power, which is reflected in constant markups, ie, there is no role for cyclicality (of fundamentals) or endogenous markups *a la* Rotemberg and Woodford (1992).

banks (and the rules for the other endogenous decision variables) are functions of the exogenous fundamentals. We assume that these reduced form pricing rules are approximately linear around steady states and can be expressed in the form depicted in equation (3.1).

We apply this setup to quarterly aggregate credit spread data from the US, Belgium, France, Germany, the Netherlands, and Spain. The samples vary slightly among countries, but generally start in the beginning or mid 1980's and end in 2007 or 2008 (a total of 96-114 observations per country). At the aggregate level, we only need measures for the risk associated with changes in the money market interest rate and the overall risks in the macro-economy. The reason is that the credit risk in the banking industry is an aggregate of bank-specific risks which are endogenous to the banks. Therefore, the state of the economy as described by the exogenous fundamentals should reflect this risk.[28] In line with, for example Claessens and Laeven (2004), we use two standard measures of the business cycle as proxies for the economy wide risk: linearly de-trended output per capita and the slope of the yield curve defined by the difference between the yields on short-term and long-term government bonds.[29] In addition, we use the inflation rate as an indicator of macro-economic stability (Demirgüç-Kunt, Laeven and Levine, 2004). The short-term money market interest rate is used to capture monetary policy (Bernanke and Blinder, 1992) and thereby also the aggregate refinancing and reinvestment risks.[30] We use unit labor costs in the financial sector to approximate the cost of labor, whereas the long-term government bond yield is taken to approximate the cost of capital. For each country, we include an appropriate foreign short-term money market interest rate to capture foreign competition and interest rate convergence.

Thus, for each country, the set of stochastic fundamentals is $\boldsymbol{f}_t = (i_t^m,\, i_t^l,\, i_t^s,\, i_t^f,\, y_t,\, \pi_t,\, w_t)'$, where i_t^m is the short-term money market interest rate, i_t^l and i_t^s are the long-term and short-term secondary market government bond yields respectively, i_t^f is an appropriate foreign short-term money market interest rate, y_t is output per capita,[31] π_t is the CPI inflation rate, and w_t is unit labor costs in the financial sector. Note, that the slope of the yield curve, $i_t^l - i_t^s$, is in the information set, since including both $i_t^l - i_t^s$ and i_t^l is equivalent to having both rates unrestricted. Robustness is checked by using the unemployment rate, the GDP deflator inflation rate, and the wage rate in place of per-capita output, the CPI inflation rate, and unit labor costs

[28] We verify (Section 5.2) that the long-run variation of US charge-off rates and delinquency rates are explained by the business cycle measures that we use to capture economy wide risk.

[29] Stock and Watson (1989) discuss different leading indicator and find that the yield curve has predictive power over real business cycle variables.

[30] We do not include measures of money market interest rate volatility, such as standard deviations from a rolling regression. There are two reasons for this. First, since we model the money market interest rate and estimate its second moment, it would be inconsistent to include it as a variable (in fact, we find no evidence of ARCH in our VAR). Second, even if the variance of the money rate was time varying, it would still be a stationary variable and can, thus, only have limited explanatory power over a non-stationary credit spread.

[31] We do not de-trend output per capita at the outset but rather include a linear trend in the cointegration space.

respectively. Detailed description of the variables is delegated to Appendix B.

In addition to the stochastic variables, we use impulse dummies and level (or trend) break dummies to capture policy interventions and institutional changes in the various financial intermediation sectors.[32] We distinguish between two types of deterministic effects: (i) deterministic breaks which affect bank conduct, namely, those affecting the orthogonal stochastic trend, and (ii) other deterministic effects which affect financial spreads but do not change conduct. This distinction can be performed in practice by estimating s_t^C from a model with no deterministic breaks and testing the significance of break dummies on the stationary variable Δs_t^C. Significant *deterministic* breaks in s_t^C belong to the first type. Once, all possible deterministic breaks in s_t^C are modeled, other potential deterministics belonging to the second type can be investigated. For example, impulse dummies, corresponding to policy interventions, often belong to the second type, since their effects are typically transitory. We report breaks of the first type in the main text, and refer to Appendix C for full account of all other deterministics that were tested.

5.2 The US

We estimated (4.5) using U.S. data over the sample period 1982:2-2007:4, with $\boldsymbol{x}_t = (p_t, i_t^m, i_t^l, i_t^s, i_t^f, y_t, \pi_t, w_t)'$, three centered seasonal dummy variables, an unrestricted constant, and a linear trend restricted in the cointegration space.[33] Figure 1 plots the raw US credit spread, p_t.

Initial findings suggested that three lags ($k = 3$) were sufficient to ensure that there were no significant misspecification in the model, apart from a rejection of normality due to three outliers. These outliers were accounted for by adding impulse dummy's to $\boldsymbol{d}_t^\Phi$ of Equation (4.5). The dummies did not affect our measure of long-run conduct and are hence described in detail in Appendix B.

The high dimension of the estimated VAR decreases the precision of the estimates (the number of parameters estimated in each equation is $kp + l = 32$). In order to reduce the dimension of the system, we tested homogeneous cointegration between the interest rates. Homogeneously cointegrated variables contain the same stochastic trends with identical loadings, implying that one of them is sufficient to represent the long-run information contained in all. We found that the federal funds rate (i_t^m), the short-run government interest rate (i_t^s), and the foreign rate (i_t^f) were homogeneously cointegrated ($\chi^2(10) = 15.2$, and p-value 0.13) independently

[32] We only consider structural breaks that are of direct relevance for the financial spread since other structural breaks are indirectly accounted for through $\boldsymbol{f}_t$.

[33] A longer sample is available for the US. However, there was considerable evidence of a structural break in the early 80's. Moreover, there were also several interests rate hikes during that period causing problems with ARCH in longer samples.

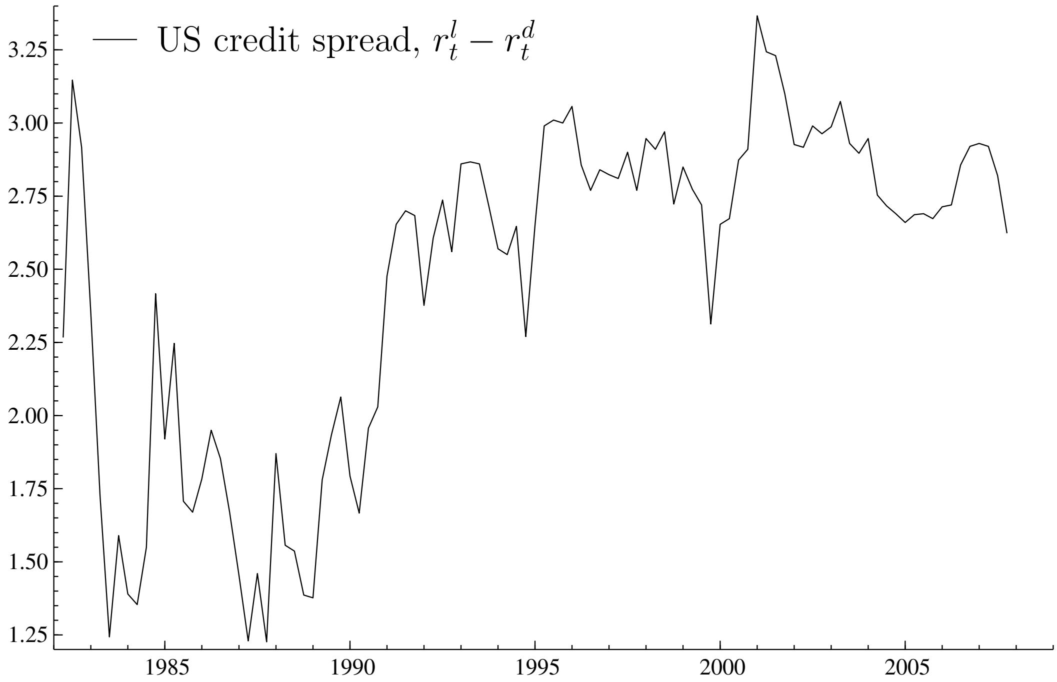


Figure 1: The raw US credit spread for the time period 1982:4–2007:4

of variations in both the choices of rank and sample. We chose i^m_t as representative of these interest rates and excluded both i^s_t and i^f_t from $\boldsymbol{x}_t$.[34]

We re-estimated the system with $\boldsymbol{x}_t = (p_t, i^m_t, i^l_t, y_t, \pi_t, w_t)'$, $k = 3$, and the same deterministic drifts as before (including the dummies). There were no significant misspecification in the model. The likelihood ratio test for the rank of Π (trace test) is reported in Table 1. The trace tests suggests $r = 3$, although $r = 2$ is also borderline accepted, implying that at least some of the variables are integrated and possibly cointegrated. Imposing $r = 3$, we tested each variable for stationarity. These tests are reported in the first row of Table 2. The table reveals that stationarity is rejected in all variables at the 5% significance level. Thus, all variables are integrated (of the first order) implying that some of the variables are cointegrated.

[34] Each of these interest rates may of course contain *stationary* information orthogonal to the others. However, given our objectives, this should not matter for our results. In fact, all results in this section are invariant to whether i^s_t or i^f_t are retained in the analysis.

Table 1. **The likelihood ratio test for the rank of II (trace test).** The λ_i are the eigenvalues from the reduced rank regression (see Johansen, 1996). The column 'Trace95' provides the 5% critical values of the trace test distribution.

r	λ_i	Trace	Trace95	p-value
0	0.46	169.31	117.45	0.00
1	0.33	107.84	88.55	0.00
2	0.29	67.82	63.66	0.02
3	0.15	32.96	42.77	**0.34**
4	0.11	16.51	25.73	**0.46**
5	0.05	4.68	12.45	**0.65**

Table 2. **Tests of stationary (Stat), long-run exclusion (Excl).** The numbers are p-values of the null hypothesis.

Test/Var	p_t	i_t^m	i_t^l	y_t	π_t	w_t
Stat	0.00	0.00	0.00	0.00*	0.00	0.00*
Excl	0.00	0.00	0.00	0.00	0.00	0.00

*Includes a linear trend.

We are mainly interested to know if p_t cointegrates with some of the variables in $\boldsymbol{f}_t$. Entries in the second row of Table 2 test the variables for long-run exclusion as described in Section 4. Table 2 reveals that *none* of the variables can be long-run excluded, implying that *all variables are cointegrated with at least one other variable* in the system. Thus, it appears that the stochastic trends in the credit spread can be accounted for by our set of fundamentals. This would imply that conduct in the US financial intermediation sector has been stable in the long-run.

However, this result is not robust to the choice of rank. If $r = 2$ was chosen instead, long-run exclusion of p_t would not have been rejected (p-value 0.06). In addition, even under $r = 3$ we find an estimate of C_{11} equal to 0.57 with a t-value of 2.98. Insights into these seemingly ambiguous results can be gained by plotting the stochastic component of the credit spread related to long-run conduct, s_t^C. This is done in Figure 2. With the exception of a short down turn in 1986–1989, the figure reveals a clear positive trend in s_t^C before 1997:1. However, from 1997 onward the trend becomes negative. This break in trend coincides with the Riegle-Neal interstate banking and branching efficiency act of 1994 which allowed banks to establish interstate branches (Kroszner and Strahan, 1999). The Riegle-Neal act is widely believed to have enhanced competition in the banking sector. Studies show that non-interest costs, wages, and loan losses all declined in the aftermath of branching reform (Jayaratne and Strahan, 1998; Kroszner, 2008). These cost reductions led, in turn, to lower loan prices, while deposit interest rates changed little.[35] Although the act was passed in September 1994, it seems reasonable that there should be a lag before the full effect of the act had taken place. To control for the Riegle-Neal act, we include a broken trend from 1994:4 onward in the set

[35] This depicts the effect of fundamentals on margins.

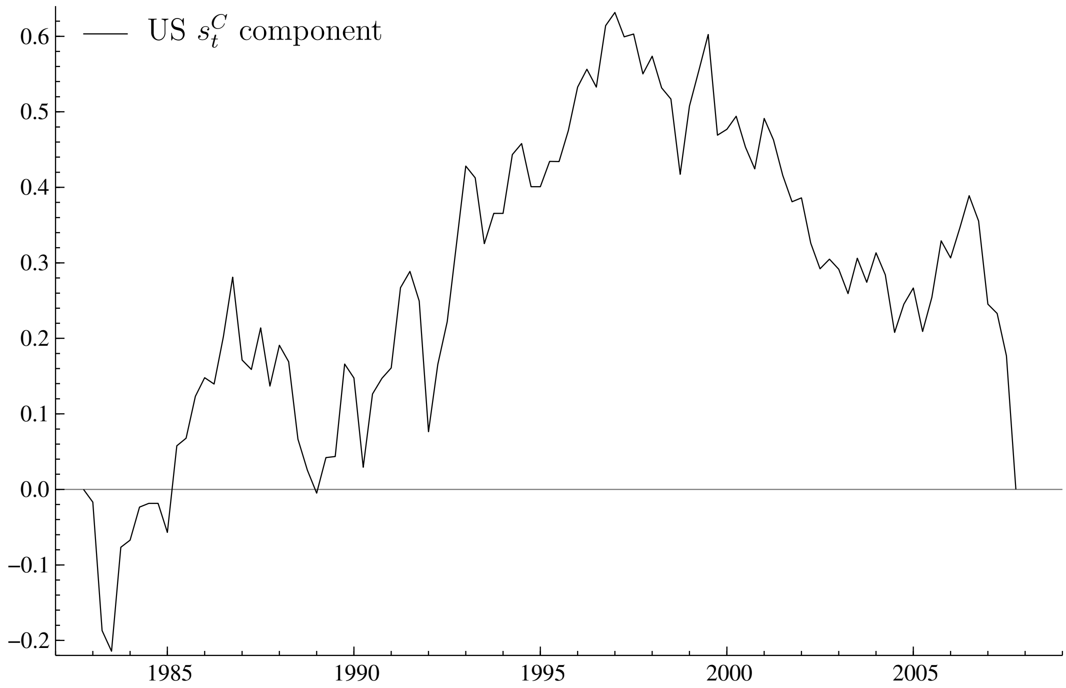


Figure 2: The stochastic trend of the US credit spread related to long-run conduct, s_t^C. Note that the figure starts and ends in the origin by construction.

of fundamentals.[36] The coefficients of both the trend and the broken trend were approximately equal to 0.03 (with corresponding t-values 5.88 and -5.83 respectively). Thus, the effect of the Riegle-Neal act was to end the 1.0–1.5% trend increase in the financial spread during 1983–1995, which is clearly visible in Figure 1. Including the broken trend did not change the results from the rank test statistic. However, with the broken trend in place, the test for long-run exclusion of p_t was rejected even when $r = 2$. Moreover, the estimate of C_{11} dropped to 0.22 with a corresponding t-value of 1.22, thus affirming stable long-run conduct.

With the broken trend in the model, we calculated both s_t^C and the deterministic trend, $\boldsymbol{m}^{C\prime}\boldsymbol{d}_t$.[37] Figure 3 depicts the measure, $s_t^C + \boldsymbol{m}^{C\prime}\boldsymbol{d}_t$, which we refer to as the *development of conduct* henceforth, and the development of the 'raw' spread $(r_t^l - r_t^d)$. Figure 3 demonstrates that the largest factor of conduct development in the US is $\boldsymbol{m}^{C\prime}\boldsymbol{d}_t$ while s_t^C plays a more modest role, which is in line with the finding of an insignificant orthogonal stochastic trend. In fact, the deterministic trend was estimated at -0.031 (t-value -0.86), which implies a change in the $\boldsymbol{m}^{C\prime}\boldsymbol{d}_t$ component of approximately -0.70% over the estimation period. This should be compared with $\left|s_t^C\right|$ which was less than

[36] The broken trend can be interpreted as a latent fundamental which was not initially included in the analysis. We also experimented by initializing the trend break in all quarters between 1994:4–1997:1. The results were virtually identical. Thus, while there is some uncertainty as to the actual break date, the effects of the Riegle-Neal act are unambiguous.

[37] We concentrated on the deterministic trend and disregarded other deterministics, stemming from the impulse dummies for instance. The reason is that the latter only have very minute effects.

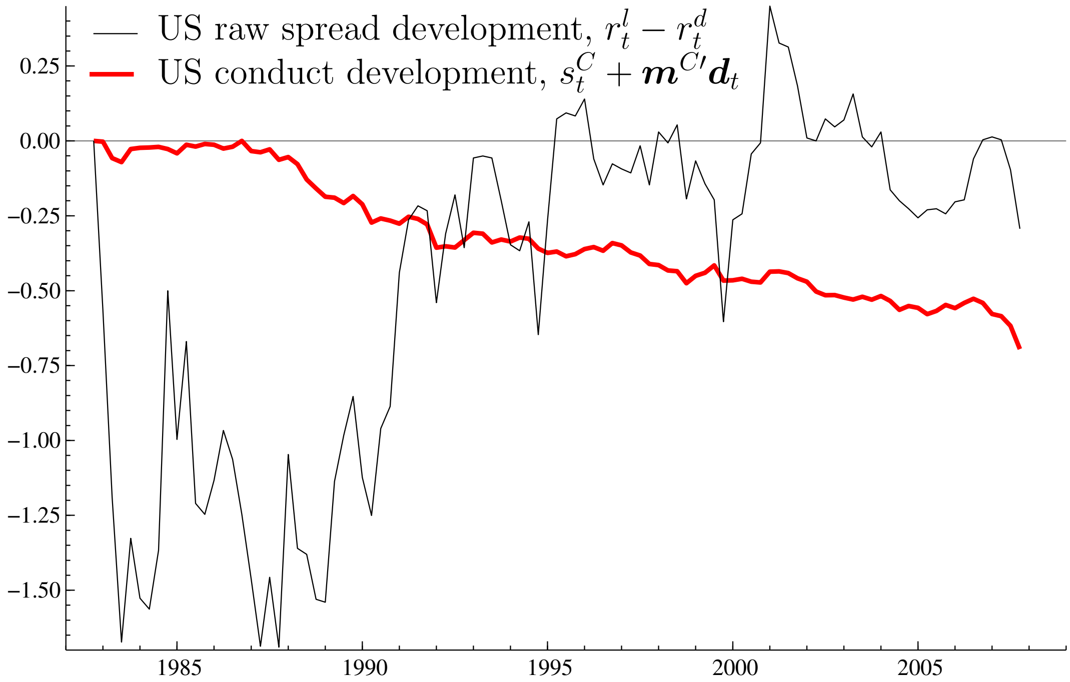


Figure 3: The US development of conduct and the raw credit spread. The financial spread is level adjusted to start at the origin in the initial period.

0.14% for any t. However, the magnitude of $\boldsymbol{m}^{C\prime}\boldsymbol{d}_t$ should be viewed with some caution, since the estimate of the deterministic trend was insignificant.

The results so far suggest that the (sub) set of fundamentals used in the analysis is sufficient to *fully account for the stochastic trends in US credit spreads*, at least once the Riegle-Neal act is controlled for. This evidence implies that conduct in the US financial intermediation sector has been stable in the long-run.

We checked the robustness of the aforementioned results by trying different sample periods and by using the unemployment rate, the GDP deflator inflation rate, and the wage rate in place of output per capita, the CPI inflation rate, and unit labor costs. There were only minor quantitative changes to the results. In addition, since two direct measures of market risk for lending, the charge-off rate and the delinquency-rate, were available from 1985:1– onward, we tested if the set of fundamentals could capture the stochastic trends in these measures.[38] We found that both measures were cointegrated with the yield curve (where i_t^m substitutes for i_t^s) and per-capita output, ie, with the variables depicting business cycles and economy wide risk. Thus, neither of these measures contains more long-run information than is already contained in the set of fundamentals.

Finally, it is instructive to compare our measure of conduct development with the, conventionally used, raw credit spread. Figure 3 demonstrates that raw credit spreads have been steadily increasing from mid 80's and

[38] That is, we first modeled $\tilde{\boldsymbol{x}}_t = (c_t^j, i_t^m, i_t^l, y_t, \pi_t, w_t)'$ by (4.5), where $j = c, d$, c_t^c is the charge-off rate, and c_t^d is the delinquency rate (see Appendix B). We then tested c_t^j for difference stationarity and cointegration with the cyclical measures in $\boldsymbol{f}_t$.

thus appear to reflect increasing market power. However, according to our methodology, these level changes in credit spreads have been propagated by changes in the fundamentals and are thus not indicative of increases in anti-competitive behavior as the measure of conduct development points to a small and (insignificant) declining margins. Hence, raw credit spreads seem to be poor descriptors for changes in market power as they appear to reflect changes in the fundamentals rather than changes in conduct. Our results highlight the impotence of correctly specifying the vector of fundamentals and its interrelationship with conduct in the determination of markups as our methodology enables. Failure to disentangle the interaction between fundamentals and conduct may produce results often obtained in applied (banking) market studies which indicate that relationships among (various measures of) competition and markups (net interest margins) deteriorate when trying to control for some factors such as regulatory restrictions or some macroeconomic factors (see *eg*, Demirgüç-Kunt, Laeven and Levine, 2004). Moreover, our methodology highlights the crucial importance fundamentals can exert on the measurement of markups and the related notion of competition intensity and which can provide a useful guide for public policy. Increasing margins are traditionally taken to be indicative of excessive increase of market power or collusion (coordinated behavior) when in fact it may be explained by changes of exogenous fundamentals. Thus, from a competition and regulatory policy perspective it is useless to go after coordinated behavior if firms may just be adjusting non-cooperatively to changing fundamentals.

5.3 The European countries

This section presents the results from Belgium (BE), France (FR), Germany (GE), the Netherlands (NL), and Spain (SP). There are minor differences in the variable definitions between the countries reflecting data availability.[39] Detailed data definitions and sources are provided in Appendix B. In addition, initial modeling of the data produced results that had bearings on the choices of variables in each country. For instance, only seasonally adjusted versions of benchmarked unit labor costs in the financial sector were available for France and the Netherlands over the full sample period. Unfortunately, the adjustment methods of the OECD appears to have introduced near $I(2)$ trends in these variables. Thus, for these countries we report the results from using private sector wages instead. Also, the short-term interest rate and the money market interest rate were homogeneously cointegrated in every country except for Spain. Hence, we reduced the dimension of the system in these countries by excluding the short-term interest rate. The main results below were invariant to any of these choices.

[39] The greatest differences are between Germany and the other European countries due the the German reunification in 1990. For Germany, we generally favored indicators with a consistent definition over the whole sample rather than using 'raw' measures.

The final sets of variables used in the analysis were $\boldsymbol{x}_t^{j_1} = (p_t, i_t^m, i_t^l, i_t^f, y_t, \pi_t, w_t)'$ for j_1 = BE, GE, $\boldsymbol{x}_t^{j_2} = (p_t, i_t^m, i_t^l, i_t^f, y_t, \pi_t, \tilde{w}_t)'$ for j_2 = FR, NL where $\tilde{w}_t$ is the wage rate of the private sector, and $\boldsymbol{x}_t^{SP} = (p_t, i_t^m, i_t^l, i_t^s, i_t^f, y_t, \pi_t, w_t)'$. Unrestricted constants, linear trends restricted to the cointegration spaces, and centered seasonal dummies were also included in each model. There were no serious misspecification in any of the models. However, initial modeling revealed some outliers which were accounted for by including dummy variables in the same way as in Section 5.2 (these dummies are discussed in Appendix B).

Table 3 summarizes the main modeling choices and statistical findings for each country. The table shows that the variables in each country are integrated (of the first order) and that at least some of them are cointegrated. To distinguish between stable and changing long-run conduct, we need to investigate whether p_t in each country is cointegrated with the fundamentals. To this end, Table 4 reports the results from testing long-run exclusion of the financial spread and provides the C_{11} estimates with corresponding t-values for each country. The evidence appearing in the table unambiguously suggest that p_t is not cointegrated with the fundamentals for Belgium, France, and the Netherlands, ie, there are significant s_t^C components in these countries. Germany and Spain both have significant C_{11} elements, but are not long-run excludable.

Table 3. **Statistical findings for the European countries.**
The row labeled 'Lags (k)' reports the choice of lag-length. The row labeled 'CI-rank (r)' provides the results from the trace test, and the row labeled 'Non-Stat' reports variables for which stationarity was rejected.

	BE	FR	GE	NL	SP
Sample	80:2–07:3	84:2–07:4	80:2–07:4	80:2–07:3	82:3–07:4
Lags (k)	2	2	2	2	2
CI-rank (r)	3	2	4	3	4
Non-Stat	All	All	All	All	All

Table 4. **Tests of long-run exclusion of the financial spreads and $\mathbf{C_{11}}$ estimates with corresponding t-values for the European countries.**
The numbers in the row labeled 'Excl' the p-values of the null hypotheses that p_t can be excluded from the cointegration spaces.

	BE	FR	GE	NL	SP
Excl	**0.28**	**0.06**	0.00	**0.06**	0.00
C_{11}	0.81	0.71	0.22	0.86	–0.61
	(7.22)	(6.91)	(2.64)	(5.16)	(–5.20)

It is possible that some of the results exhibited in Table 4 may be due to latent institutional events. Figure 4 plots the s_t^C components of each country. As can be seen from the figure, there is potentially a negative deterministic level shift in the Spanish orthogonal stochastic trend (panel (e)) at 1993:1. Interestingly, this negative level shift occurs at the same time that

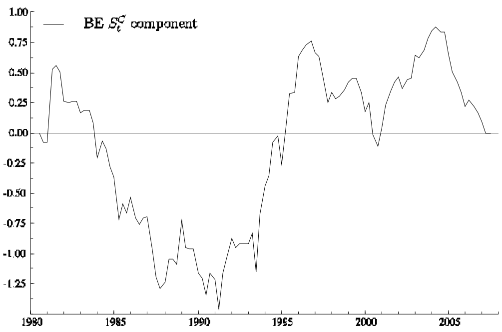
Spain implemented the Second Banking Directive and liberalized international capital flows. We included a level shift dummy restricted to the cointegration space at this date. The dummy significantly decreased the Spanish financial spread by 1.59% (t-value -5.35). Moreover, the dummy had no effect on the cointegration rank, but increased the estimate of C_{11} from -0.61 to -0.18 with a corresponding t-value of -2.18, ie, there were only border line significant conduct change in Spain with the break dummy in place. There are no obvious deterministic breaks in the orthogonal stochastic trends of the other countries.[40] Overall, the results indicate that the included European countries can be divided into two categories according to whether their banking sectors exhibited stable or changing long-run conduct. The first category consists of Germany and Spain, whereas the second consists of Belgium, France, and the Netherlands.

The *developments of conduct* ($s_t^C + \boldsymbol{m}^{C'}\boldsymbol{d}_t$) and the 'raw' credit spreads ($r_t^l - r_t^d$) of each country are depicted in Figure 5.[41] The figure reveals that Belgian conduct development (panel (a)) has steadily increased by 6% since 1980, indicating a significant reduction in competition. In stark contrast, the conventional raw credit spread has declined by 3–4% during the same period, indicating an increase in competition. Thus, in the Belgian case, credit spreads or margins would have been substantially larger by the end of the sample period without pressure propagated by the exogenous changes in fundamentals which served as mitigating factors on conduct. In contrast, French conduct development (and to some extent Dutch conduct development) has more or less followed the development in the raw credit spread (panel (b)). This indicates that stochastic trends originating in the fundamentals only have minor impacts on the long-run development of French raw credit spreads, or conversely, that French credit spreads are mostly explained by changes in long-run conduct. French conduct development has fluctuated somewhat during the sample period but essentially returned to its initial level, perhaps indicating that banks have been successful in reducing competition for shorter periods. Dutch conduct development (panel (c)) has decreased by 3% compared to a decrease of 1.5% in the raw spread during the same period. Thus, Dutch banks have become more competitive than is indicated by the raw spread measure. Figure 5 also reveals that the conduct components of both Germany and Spain (panels (c) and (e), respectively) are minor compared to the overall developments of the raw credit spreads in each of these countries, implying relatively stable long-run conduct.[42] Together these results affirm the difficulties of viewing the conventionally utilized raw credit spreads as indicative of market power. Additionally, results point to a great deal of country-specific variation between conduct-related margins and raw

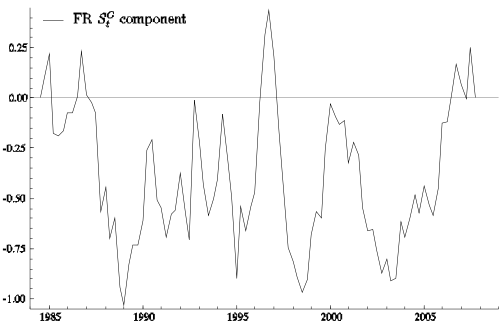
[40] Inspection of panel (a) in Figure 4 may suggest a possible level break in the Belgian s_t^C component as well. However, this level shift takes place smoothly over the period 1994–1997. Indeed, including a level shift dummy for any date in this interval yields insignificant results.

[41] As in the analysis of US data, we concentrated on the deterministic trend and disregarded other orthogonal deterministics.

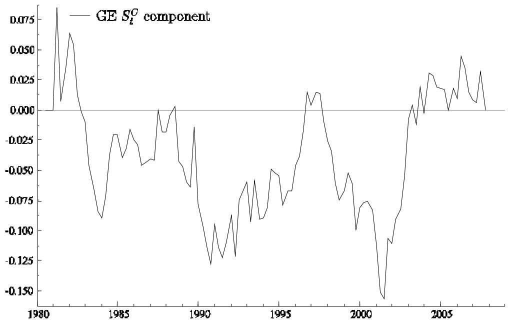
[42] The findings pertaining to the relative stability of conduct in the German, and Spanish banking sectors compared to the French and Dutch banking sectors are quite consistent with recent findings of relative competitiveness of these sectors in other studies (van Leuvensteijn et al, 2007).



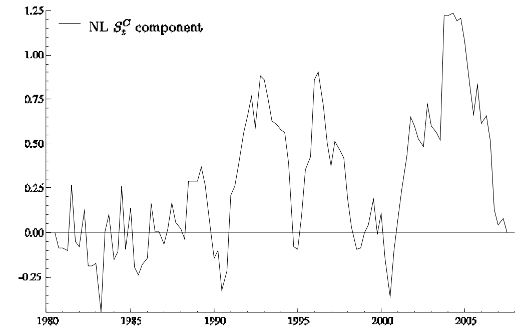
(a) Belgium



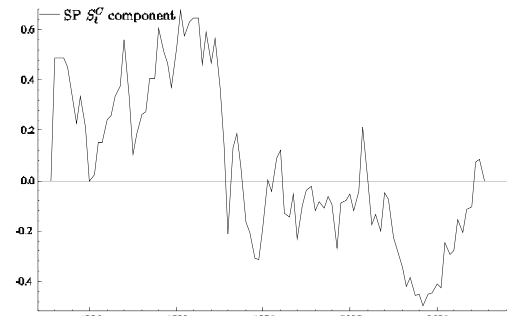
(b) France



(c) Germany



(d) Netherlands



(e) Spain

Figure 4: The stochastic trends of the European credit spreads related to long-run conduct, s_t^C. Note that the figures start and end in the origin by construction and have different scales.

margins stemming from differential country-specific shocks to fundamentals and reactions to such which indeed are accommodated by our model. The reported differences among the various countries may reflect differential 'stocks' of histories, institutional, legislative, capital markets imperfections, and political settings and the particular interaction among these. As the mix of industries differ across countries, different relative factor productivities dictate different relative reliance on external finance and thus affect the relative ability of banks to extract rents. Of course any shock to fundamentals may thus exert different effects on price changes in general and on changes of conduct related margins in particular.[43]

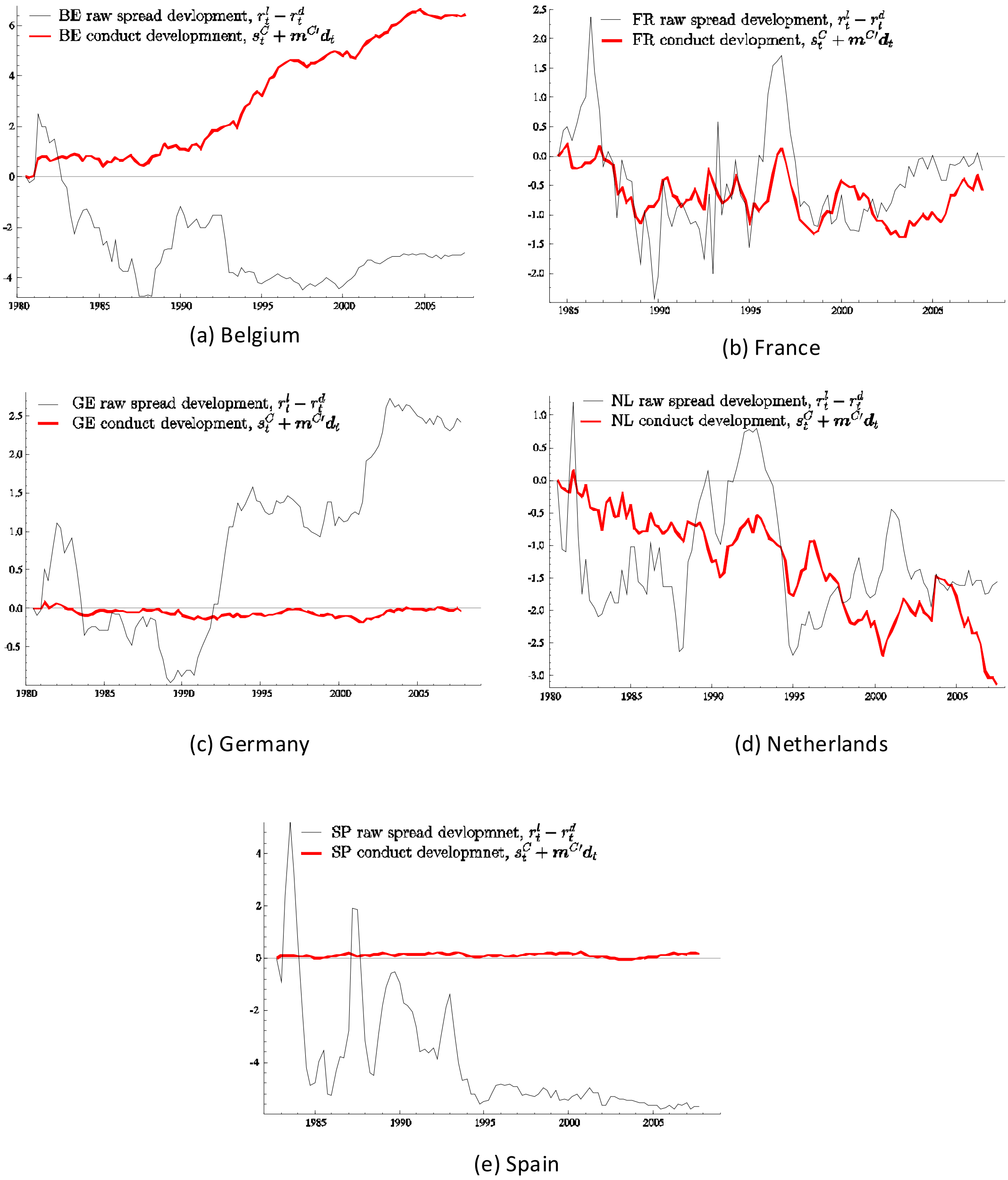
5.3.1 Conduct or latent fundamentals?

Results in Table 4 suggest that the empirical set of fundamentals cannot fully account for the stochastic trends in Belgian, French and Dutch credit spreads. So far we have interpreted such results as reflecting changes in long-run conduct. However, another possibility is that they reflect latent fundamentals. If the former explanation is correct, there should be significant non-linearities in the data and a (correctly specified) regime shift model should yield stationary residuals, whereas such remedies should be of little avail if the latter explanation is true.

In this section, we test the Belgian, French and Dutch data for the null hypothesis of linearity against the alternative hypothesis of a cointegrated STR-model. To this end we employ the linearity test by Choi and Saikkonen (2004), which is based on Taylor series approximations[44] of the transition functions and the assumption of cointegration, either under the null or the alternative. Thus, the residual form an estimated STR model should, strictly speaking, be tested for stationarity *prior* to applying the test. However, the linearity test can be used to uncover the transition variables in the absence of strong theoretical priors, which greatly reduces the dimension of the non-linear estimation problem. The reason is that all non-linearities originate in the transition functions under the STR alternative. Hence, we begin by applying the Choi and Saikkonen test to STR models where the transition variable is sequentially taken to be one of the fundamentals. If the null hypotheses cannot be rejected, there is no evidence of non-linearity and we conclude that latent fundamentals are the likely explanation of the results in Table 4. However, if some of the tests reject, we use the corresponding variables f_{i_ψ}, where $i_\psi \in \{1, ..., q-1\}$ and $\psi = 1, ..., \bar{\psi}$, as transition variables to estimate a

[43] The differences in country-specific results are quite consistent with results arrived at by studies (collected in a special issue of the Journal of Banking and Finance 30 (7) 2006, 'Banking and Finance in an Integrating Europe') which point to the disparities across European countries' banking sectors and which can be attributed to differences among the various localities in which banks operate. Kroszner and Strahan (1999) discuss the interplay between politics and economics and the effects of such on banking outcomes.

[44] Hence, the alternative hypothesis is some STR model in general, rather than a particular STR specification.



(a) Belgium

(b) France

(c) Germany

(d) Netherlands

(e) Spain

Figure 5: The developments of conduct and the raw credit spreads of the European countries. To facilitate the comparison, the financial spreads are level adjusted to start at the origin.

simple two regime STR-model of the form

$$p_t = \boldsymbol{m}_j' \boldsymbol{d}_t + \boldsymbol{\beta}_1' \boldsymbol{f}_t + R_t(\psi_t) \boldsymbol{\beta}_2' \boldsymbol{f}_t + v_t^{STR} \tag{5.1}$$

where

$$\begin{aligned} R_t(\psi_t) &= \frac{1}{1 + e^{-\kappa_0 \psi_t}} \\ \psi_t &= \prod_{\psi=1}^{\bar{\psi}} \left(f_{i_\psi, t} - \kappa_\psi \right) \end{aligned}$$

the deterministic term $\boldsymbol{m}_j' \boldsymbol{d}_t$ consists of a constant and seasonal dummies, and the disturbance term v_t^{STR} is assumed to satisfy the assumptions in Saikkonen and Choi (2004). Next, we test the residuals obtained from the estimated STR models for stationarity.[45] If stationarity cannot be rejected, the results from the linearity tests apply, and we can conclude that STR-dynamics can account for the impression of an additional stochastic trend in the credit spreads. However, if stationarity is rejected, we again conclude that latent fundamentals may explain the Belgian, French and Dutch results.

Table 5 reports the results from the linearity tests. As can be seen from the table, linearity is rejected in all three countries. Moreover, the transitions between equilibria generally depend on the different types of interest rates, whereas the other variables do not seem to have a large impact on the transitions. It seems likely that the relevant thresholds for the different interest rates within countries are close to each other. Hence, one interest rate may be sufficient as a transition variable. To this end we chose the long-term interest rate, ie, we set $\bar{\psi} = 1$ and $\psi_t = i_t^l - \kappa_1$ in (5.1).[46] Table 6 reports the results from testing stationarity on the residuals obtained from estimating (5.1) for Belgium, France, and the Netherlands. The table shows that the null hypothesis of the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test for stationarity cannot be rejected at the 5% significance level in any of the cases, whereas the null hypothesis of the ADF (Augmented Dickey-Fuller) test for non-stationarity is rejected at the 5% significance level in all cases. These results suggests that STR type dynamics can fully account for the stochastic trends in the Belgian, French, and Dutch credit spreads. Thus, it is not latent fundamentals but rather changes in long-run conduct that explain the Belgian, French, and Dutch results.

[45] We do not report the STR-model estimates since their interpretation requires a theoretical framework. Moreover, disentangling $\boldsymbol{\eta}_e$, $e = 1, 2$, and $\boldsymbol{\theta}$ from $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ in (5.1) is difficult without a markup measure. Instead, we use the specific two regime STR-model in (5.1) to investigate if regime shift dynamics can indeed fully account for the stochastic trends in the credit spreads (see the main text). The details of the estimations are available upon request.

[46] We also experimented with other choices of ψ_t based on the results in Table 5 but the results were invariant to these choices.

Table 5. **Tests of linearity against a STR alternative for Belgium (BE), France (FR), and the Netherlands (NL).**
The column labeled 'ψ_t' provides the transition variable, the column '$\chi^2_{0.95}$' provides the 5% critical value for the χ^2 distribution with $q-1=0$ degrees of freedom, the columns 'τ' provides the value of the test statistic, and the columns 'p-val' provides the p-values of the null hypothesis where bold values indicate rejection a 5% significance level.

		BE		FR		NL	
ψ_t	$\chi^2_{0.95}$	τ	p-val	τ	p-val	τ	p-val
i_t^m	12.59	13.01	0.04	22.10	0.00	22.33	0.00
i_t^l	12.59	16.11	0.01	29.33	0.00	23.09	0.00
i_t^f	12.59	12.72	**0.05**	29.38	0.00	21.34	0.00
y_t^*	12.59	8.48	**0.21**	2.51	**0.87**	11.92	**0.06**
π	12.59	4.75	**0.57**	15.58	0.02	6.37	**0.38**
w_t^*	12.59	5.33	**0.50**	11.75	**0.07**	14.38	0.03

* Linear trend removed.

Table 6. **KPSS and ADF tests on the residuals estimates of (5.1) on Belgian (BE), French (FR), and Dutch (NL) data**
Column 'τ_i', $i = KPSS, ADF$, reports the test statistic and 'Crit. 5%' its corresponding 5% critical value.

	τ_{KPSS}	Crit. 5%	τ_{ADF}	Crit. 5%
BE	0.09	0.46	**-6.08**	-2.89
FR	0.06	0.46	**-5.20**	-2.89
NL	0.06	0.46	**-6.60**	-2.89

6 Conclusions

In this paper we suggested a VAR based approach to detect shifts in oligopolistic long-run conduct when data are difference stationary. Such shifts are increasingly likely to occur with the degree of market power held by firms and may reduce the applicability of existing methods for measuring and analyzing markups and the associated competitive nature. The approach is based on the idea that prices and fundamentals are cointegrated under stable conduct regimes, whereas cointegration breaks down when there are long-run changes in conduct since they introduce the appearance of an additional stochastic trend into prices. In this respect, our approach can be interpreted as a binary test of market power under changing equilibrium configurations.

In addition, we demonstrated that the VAR methodology can be used to filter out the component in markups which is due to changes in long-run conduct from those explained by various fundamentals. This component measure can be useful in detecting periods of anti-competitive behavior. The advantage of our approach is in that it is easy to apply, does not require prior assumptions on market structure and does not necessitate the estimation of conduct parameters which is quite problematic in the presence of multiple and changing equilibria. However, the set of fundamentals that is used must be sufficiently broad to capture all long-run variation in prices *during stable regimes*. Moreover, it is important to safeguard against possible influences of latent fundamentals on the resultant measured conduct related markups. This can be done through proper testing as offered in the present study.

We applied our approach to the US and five major European financial intermediation sectors. We found that credit spreads and fundamentals were cointegrated in the cases of the US, Germany, and Spain, whereas credit spreads and fundamentals were not cointegrated in the cases of Belgium, France, the Netherlands. We also depicted the markup components which are exclusively related to long-run changes in conduct for these countries. We document that the dynamics displayed by these components are typically substantially different from the dynamics displayed by the (conventionally used) raw credit spreads. Thus, our results indicate that conventional raw credit spreads may be highly misleading as indicators of changes in conduct and the associated changes in the degree of competition. This may exert significant implications for policies directed toward imperfectly competitive markets and market power measurements.

References

Al-Najjar, N – Baliga, S – Besanko, D (2008) **Market forces meet behavioral biases: cost misallocation and irrational pricing.** RAND Journal of Economics, 39, 214–237.

Angelini, P – Cetorelli, N (2003) **The effects of regulatory reform on competition in the banking industry.** Journal of Money, Credit and Banking, 35, 663–684.

Bai, J (2004) **Estimating cross-section common stochastic trends in nonstationary panel data.** Journal of Econometrics, 122, 137–183.

Balke, N S – Fomby, T B (1997) **Threshold cointegration.** International Economic Review, 38, 627–645.

Berger, A N – Demirgüc-Kunt, A – Levine, R – Haubrich, J G (2004) **Bank concentration and competition: An evolution in the making.** Journal of Money Credit and Banking, 36, 433–451.

Bernanke, B S – Blinder, A S (1992) **The federal funds rate and the channels of monetary transmission.** American Economic Review, 82, 901–921.

Boone, J (2008) **A new way to measure competition.** The Economic Journal, 118, 1245–1261.

Bresnahan, T F (1987) **Competition and collusion in the American automobile industry: the 1955 price war.** Journal of Industrial Economics, 35, 457–482.

Bresnahan, T F (1989) **Empirical studies of industries with market power.** In Schmalensee, R and Willig, R D (eds.) The Handbook of Industrial Organization, Vol. 2, 1011–1057 (Amsterdam: North-Holland).

Camacho, M (2005) **Markov-switching stochastic trends and economic fluctuations.** Journal of Economic Dynamics & Control, 29, 135–158.

Carbó, S – Humphrey, D – Maudos, J – Molyneux, P (2008) **Cross-country comparisons of competition and pricing power in european banking.** Journal of International Money and Finance, In press.

Choi, I – Saikkonen, P (2004) **Testing linearity in cointegrating smooth transition regressions.** Econometrics Journal, 7, 341–365.

Ciliberto, F – Tamer, E (2007) **Market structure and multiple equilibria in airline markets.** (Working Paper 605723, SSRN).

Claessens, S – Demirgüc-Kunt, A – Huizinga, H (2001) **How does foreign entry affect domestic banking markets?** Journal of Banking & Finance, 25, 891–911.

Claessens, S – Laeven, L (2004) **What drives bank competition? some international evidence.** Journal of Money Credit and Banking, 36, 563–583.

Claessens, S – Laeven, L (2005) **Financial dependence, banking sector competition, and economic growth.** Journal of the European Economic Association, 3, 179–201.

Corts, K (1999) **Conduct parameters and the measurement of market power.** Journal of Econometrics, 88, 227–250.

Dalbó, P (2007) **Tacit collusion under interest rate fluctuations.** RAND Journal of Economics, 38, 533–540.

Demirgüc-Kunt, A – Laeven, L – Levine, R (2004) **Regulations, market structure, institutions, and the cost of financial intermediation.** Journal of Money, Credit and Banking, 36, 593–622.

Domowitz, I (1993) **Oligopolistic pricing: Time-varying conduct and the influence of product durability as an element of market structure.** In Norman, G and Manna, M L (eds.) The New Industrial Economics, (USA: Edward Elgar Publishing Company).

Domowitz, I – Hubbard, R G – Petersen, B (1986) **Business cycles and the relationship between concentration and price-cost margins.** RAND Journal of Economics, 17, 1–17.

Forni, M (2004) **Using stationarity tests in antitrust market definition.** American Law and Economics Review, 6, 441–464.

Galí, J (1994) **Monopolistic competition, business cycles, and the composition of aggregate demand.** Journal of Economic Theory, 63, 73–96.

Green, E J – Porter, R H (1984) **Noncooperative collusion under imperfect price information.** Econometrica, 52, 87–100.

Gual, J (1999) **Deregulation, integration and market structure in european banking.** Journal of the Japanese and International Economies, 13, 372–396.

Hall, R E (1988) **The relation between price and marginal cost in U.S. industry.** Journal of Political Economy, 96, 921–947.

Hansen, B E – Seo, B (2002) **Testing for two-regime threshold cointegration in vector error-correction models.** Journal of Econometrics, 110, 293–318.

Hansen, P R (2005) **Granger's representation theorem: A closed-form expression for I(1) processes.** Econometrics Journal, 8, 23–38.

Hassler, U – Kuzin, V (2008) **Cointegration analysis under measurement errors.** (Working paper, Goethe-University Frankfurt).

Ho, T S Y – Saunders, A (1981) **The determinants of bank interest margins: Theory and empirical evidence.** Journal of Financial and Quantitative Analysis, 16, 581–600.

Jayaratne, J – Strahan, P E (1998) **Entry restrictions, industry evolution, and dynamic efficiency: Evidence from commercial banking.** Journal of Law and Economics, 41, 239–274.

Johansen, S (1996) **Likelihood-Based Inference in Cointegrated Vector Auto-Regressive Models** (Oxford, UK: Oxford University Press).

Juselius, K (2006) **The Cointegrated VAR Model: Methodology and Applications** (Oxford, UK: Oxford University Press).

Kashyap, A – Stein, J C – Wilcox, D (1993) **Monetary policy and credit conditions: Evidence from the composition of external finance.** American Economic Review, 83, 78–98.

Kilian, L – Taylor, M P (2003) **Why is it so difficult to beat the random walk forecast of exchange rates?** Journal of International Economics, 60, 85–107.

Kroszner, R S (2008) **The effect of removing geographic restrictions on banking in the united states: Lessons for europe.** Financial Markets, Institutions & Instruments, 17, 5–12.

Kroszner, R S – Strahan, P E (1999) **What drives deregulation? economics and politics of teh relaxation of bank branching restrictions.** Quarterly Journal of Economics, 114, 1437–1467.

Laeven, L – Majnoni, G (2005) **Does judicial efficiency lower the cost of credit?** Journal of Banking & Finance, 29, 1791–1812.

Leybourne, S – Newbold, P – Vougas, D (1998) **Unit roots and smooth transitions.** Journal of time series analysis, 19, 83–97.

Nelson, C R – Piger, J – Zivot, E (2001) **Markov regime switching and unit-root tests.** Journal of Business & Economic Statistics, 19, 404–415.

Oliver, A M –Fumás, V S – Saurina, J (2006) **Risk premium and market power in credit markets.** Economics Letters, 93, 450–456.

Pakes, A (2008) **Theory and empirical work on imperfectly competitive markets.** (Working Paper 14117, NBER).

Panzar, J C – Rosse, J N (1987) **Testing for monopoly equilibrium.** Journal of Industrial Economics, 35, 443–456.

Paruolo, P (1997) **Asymptotic inference on the moving average impact matrix in cointegrated I(1) VAR systems.** Econometric Theory, 13, 79–118.

Porter, R H (1983) **A study of cartel stability: The joint executive committe, 1880–1886.** Bell Journal of Economics, 14, 301–314.

Rosenthal, R (1980) **A model in which an increase in the number of sellers leads to a higher price.** Econometrica, 48, 1575–1579.

Rotemberg, J J – Saloner, G (1986) **A super-game theoretic model of business cycles and price wars during booms.** American Economic Review, 76, 390–407.

Rotemberg, J J – Woodford, M (1991) **Markups and the business cycle.** In Blanchard, O and Fischer, S (eds.), NBER Macroeconomics Annual, Vol. 6, 63–129 (Cambridge MA, USA: MIT Press).

Rotemberg, J J – Woodford, M (1992) **Oligopolistic pricing and the effects of aggregate demand on economic activity.** Journal of Political Economy, 100, 1153–1207.

Saikkonen, P – Choi, I (2004) **Cointegration smooth transition regressions.** Econometric Theory, 20, 301–340.

Saunders, A – Schumacher, L (2000) **The determinants of bank interest rate margins: an international study.** Journal of International Money and Finance, 19, 813–832.

Silvestre, J (1993) **The market power foundations of macroeconomic policy.** Journal of Economic Literature, 31, 105–141.

Staiger, R W – Wolak, F A (1992) **Collusive pricing with capacity constraints in the presence of demand uncertaintypreview.** RAND Journal of Economics, 23, 203–220.

Stiglitz, J E (1989) **Imperfect information in the product market.** In Schmalensee, R and Willig, E (eds.), Handbook of Industrial Organization, Vol. 1, 771–847 (Amsterdam: North-Holland).

Stock, J – Watson, M (1989) **New indexes of coincident and leading indicators.** In Blanchard, O and Fischer, S (eds.), NBER Macroeconomics Annual, Vol. 4, 351–394 (Cambridge MA, USA: MIT Press).

van Dijk, D – Teräsvirta, T – Franses, P H (2002) **Smooth transition autoregressive models – a survey of recent developments.** Econometric Reviews, 21, 1–47.

van Leuvensteijn, M – Bikker, J A – van Rixtel, A – Kok Sørensen, C (2007) **A new approach to measuring competition in the loan markets of the euro area.** (Working Paper 768, ECB).

Waterson, M (1984) **Economic theory of the industry.** (Cambridge, UK: Cambridge University Press).

A Appendix: Empirical decomposition

This section shows how to obtain s_t and $\boldsymbol{m}'\boldsymbol{d}_t$ from a cointegrated VAR-model for p_t and $\boldsymbol{f}_t$. These components describe the evolution of firm conduct when $\boldsymbol{f}_t$ is perfectly observed. An expression for s_t^C (see Equation (4.8)) was derived in the main text. The terms that remain to be derived are $s_t^{C^*}$, $\boldsymbol{m}^{C\prime}\boldsymbol{d}_t$, and $\boldsymbol{m}^{C^*\prime}\boldsymbol{d}_t$.

Hansen (2005) shows that the polynomial $C^*(L)$ in (4.7) can be computed recursively by

$$\Delta C_i^* = \Pi C_{i-1}^* + \sum_{j=1}^{k-1} \Gamma_j \Delta C_{i-j}^*, \qquad i = 1,\, 2, ...$$

with initial values $C_0^* = I - C$ and $C_{-1}^* = ... = C_{-k+1}^* = -C$. Using $\Omega\Omega^{-1}\boldsymbol{\upsilon}_t = \Omega\boldsymbol{\varepsilon}_t$, $\varepsilon_t^s = \Omega_{1j}^{-1}\boldsymbol{\upsilon}_t$, and $\Omega_{j1} = (1,\, \mathbf{0}')'$ as before, we get

$$s_t^{C^*} = \sum_{i=0}^{t-1} C_{11,i}^* \Omega_{1j}^{-1} \boldsymbol{\upsilon}_t$$

The deterministic trend is slightly more complicated to derive because the first right hand term of (4.7) integrates the deterministic drift. The relationship between the deterministic drift $\Phi\boldsymbol{d}_t^{\Phi}$ and the deterministic trend $M^{\boldsymbol{x}}\boldsymbol{d}_t$ can be derived by rewriting (4.5) in terms of the de-trended variable $\boldsymbol{y}_t = \boldsymbol{x}_t - M^{\boldsymbol{x}}\boldsymbol{d}_t$ which yields

$$\Delta\left(\boldsymbol{x}_t - M^{\boldsymbol{x}}\boldsymbol{d}_t\right) = \alpha\beta'\left(\boldsymbol{x}_{t-1} - M^{\boldsymbol{x}}\boldsymbol{d}_{t-1}\right) + \sum_{i=1}^{k-1}\Gamma_i\Delta\left(\boldsymbol{x}_{t-i} - M^{\boldsymbol{x}}\boldsymbol{d}_{t-1}\right) + \boldsymbol{\upsilon}_t$$

and hence

$$\Phi\boldsymbol{d}_t^{\Phi} = \alpha\beta'^{\boldsymbol{x}}\boldsymbol{d}_{t-1} + M^{\boldsymbol{x}}\Delta\boldsymbol{d}_t - \sum_{i=1}^{k-1}\Gamma_i M^{\boldsymbol{x}}\Delta\boldsymbol{d}_{t-i} \tag{A.1}$$

Note that in general $\boldsymbol{d}_t^{\Phi} \neq \boldsymbol{d}_t$ since $\boldsymbol{d}_t^{\Phi}$ is a function of lagged and differences $\boldsymbol{d}_t$.

It can be seen directly from (4.2) that $\Omega_{1j}^{-1}\Phi\boldsymbol{d}_t^{\Phi} = (1 - \lambda(L))\,\boldsymbol{m}\boldsymbol{d}_t$ isolates the drift of μ_t. From (4.7) we see that the deterministic trend in $\boldsymbol{x}_t$ is given by

$$\begin{aligned} M^{\boldsymbol{x}}\boldsymbol{d}_t &= C\sum_{i=0}^{t-1}\Phi\boldsymbol{d}_{t-i}^{\Phi} + \sum_{i=0}^{t-1}C_i^*\Phi\boldsymbol{d}_{t-i}^{\Phi} \\ &= C\Omega\sum_{i=0}^{t-1}\Omega^{-1}\Phi\boldsymbol{d}_{t-i}^{\Phi} + \sum_{i=0}^{t-1}C_i^*\Omega\Omega^{-1}\Phi\boldsymbol{d}_{t-i}^{\Phi} \end{aligned} \tag{A.2}$$

and, hence, it would be tempting to calculate $\boldsymbol{m}'\boldsymbol{d}_t$ by picking out the $\Omega_{1j}^{-1}\Phi\boldsymbol{d}_t^{\Phi}$ elements from the first line of (A.2). Unfortunately, this is incorrect. The reason for the difficulty is that factor $\alpha\beta' M\boldsymbol{d}_{t-1}$ of $\Phi\boldsymbol{d}_{t-i}^{\Phi}$ in (A.1) cancels when it is multiplied by C in the first right hand term of (A.2). However, the corresponding part, $\Omega_{1j}^{-1}\alpha\beta' M \boldsymbol{d}_{t-1}$, of $\Omega_{1j}^{-1}\Phi\boldsymbol{d}_t^{\Phi}$ *does not* cancel when it is multiplied by $C_{1j}\Omega_{j1} = C_{11}$. Hence, the factor $\alpha\beta' M \boldsymbol{d}_{t-1}$ must be removed from $\Phi\boldsymbol{d}_{t-i}^{\Phi}$ before multiplying by Ω_{1j}^{-1}. This can be achieved by using the identity $I = \alpha(\alpha'^{-1}\alpha' + \alpha_{\perp}(\alpha_{\perp}'\alpha_{\perp})^{-1}\alpha_{\perp}'$ to decompose Φ into the parts $\alpha(\alpha'^{-1}\alpha'\Phi = \alpha\beta' M$ and $\alpha_{\perp}(\alpha_{\perp}'\alpha_{\perp})^{-1}\alpha_{\perp}'^{C}$. Thus, the deterministic markup is given by the sum of

$$\boldsymbol{m}^{C\prime}\boldsymbol{d}_t = C_{11}\sum_{i=0}^{t-1}\Omega_{1j}^{-1}\Phi^{C}\boldsymbol{d}_{t-i}^{\Phi}$$

and

$$\boldsymbol{m}^{C*\prime}\boldsymbol{d}_t = \sum_{i=0}^{t-1}C_{11,i}^{*}\Omega_{1j}^{-1}\Phi\boldsymbol{d}_{t-i}^{\Phi}$$

Collecting results, we find

$$s_t + \boldsymbol{m}'\boldsymbol{d}_t = C_{11}\sum_{i=0}^{t-1}\Omega_{1j}^{-1}\left(\boldsymbol{v}_t + \Phi^{C}\boldsymbol{d}_{t-i}^{\Phi}\right) + \sum_{i=0}^{t-1}C_{11,i}^{*}\Omega_{1j}^{-1}\left(\boldsymbol{v}_t + \Phi\boldsymbol{d}_{t-i}^{\Phi}\right)$$

Finally, we note that it is not possible to decompose the initial values in (4.7) into a part which is orthogonal with respect to the fundamentals. In fact, the initial values takes the role of a constant when $\boldsymbol{x}_t$ is non-stationary.

B Appendix: Data

The sources and definitions of the data are provided in this section. These are reported in Table B1.1

Table B1.1 **Variable definitions and sources**

Var.	Countries	Definition	Source*
r_t^l	US	Prime rate.	FRS
	BE, FR, GE, NL, SP	Retail bank interest rates, Loans to enterprises up to 1 year.	
		Harmonized definition after 2003:1.	
		Germany: excluding ex-GDR before 1991.	ES
r_t^d	US	Yield on 6-month secondary market certificates of deposits.	FRS
	BE, FR, GE, NL, SP	Retail bank deposits with agreed maturity up to 1 year.	
		Harmonized definition after 2003:1.	
		Germany: excluding ex-GDR before 1991.	ES
i_t^m	US	3-month federal funds rate.	FRS
	BE, FR, GE, NL, SP	3 month-interbank rate before 1999:1, EURIBOR 3-month after.	ES
i^l	US	Secondary market yield on 10-year T-bills.	FRS
	BE, FR, GE, NL, SP	Secondary market yield on government 10-year bonds.	ES
i_t^s	US, BE, SP	Secondary market yield on 3-month T-bills.	FRS
	FR	Secondary market yield on government 13-month T-bills.	EcS
	GE	Secondary market yield on listed Federal securities 1 year maturity.	EcS
	NL	Secondary market yield on 3-month local government bonds.	CB
i_t^f	US, GE	3-month dollar LIBOR rate.	FRS
	BE, FR, NL, SP	3-month FIBOR before 1999:1, 3-month EURIBOR after.	ES
y_t	US, FR, NL	Real GDP (deflated by the CPI index) divided by working population (15–65 years old).	BEA, ES, OECD
	BE, SP	Real GDP (deflated by the CPI index) divided by total population.	ES, OECD
	GE	Index of total industry production, 2000 = 100, divided by population (15–65 years old, constant adjusted west German level until 1991).	OECD
π_t	All countries	Log difference of consumer price index.	OECD
w_t	US	Benchmarked unit labor costs, Market services (ISIC: G to K).	OECD
	BE, GE, SP	Benchmarked unit labor costs, Financial services (ISIC: J to K).	OECD
$\widetilde{w}_t$	FR, NL	Wage rate of the private sector.	OECD
Robustness control variables:			
y_t	US, BE, FR, NL, SP	Unemployment rate.	OECD
π_t	All countries	Log difference of GDP deflator	BEA, OECD
w_t	US	Real average weekly earnings in the financial sector.	BLS
	BE, GE, SP	Hourly earnings in manufacturing.	OECD
$\widetilde{w}_t$	FR, NL	Benchmarked unit labor costs (seasonally adjusted), Financial services.	OECD
c_t^c	US	Loan charge-off rate.	FRS
c_t^d	US	Loan delinquency rate.	FRS

* Sources: Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Central Bank (CB), EuroStat (ES), EuroStats (EcS), Federal Reserve System (FRS), OECD database (OECD).

In the empirical application, we modeled several outliers by including, (i) ordinary impulse dummies taking the value one at the relevant quarter and zero otherwise, and (ii) temporary impulse dummies taking the value one in the relevant quarter and minus one in the consecutive quarter.[47] To ensure replicability, we report these dummies in Table B1.2.

Table B1.2 **Ordinary and temporary impulse dummies used in the empirical analyzes.**
Ordinary impulse dummies are labeled DYYQ, where YY are year digits and Q is the quarter digit. Temporary impulse dummies are similarly labeled DTYYQ, where T stands for temporary.

Country	Ordinary	Temporary
US	D844, D941	DT924
Belgium	D811, D824, D883, D894, D924, D931	–
France	D862, D894	DT931
Germany	D804, D811, D881	DT814
Netherlands	D811, D824, D864, D891	–
Spain	D832, D833, D854, D884, D912	DT872, DT874

The dummy variable $D844$ corresponds to relaxation of the U.S. reserve requirements. The dummies $D811$ and $D881$ correspond to monetary policy interventions in Germany, which were also transmitted to other European countries. The other European dummies mostly capture foreign interest rate effects. For example, the dummy $D804$ captures a liquidity crunch in the U.K. The dummies $D824$, $D883$, $D891$, and $D894$, account for the fact that the members of ERM (European Exchange Rate Mechanism) and EMS (European Monetary System) had to adjust to the German interest rates. The dummies in 92-93 capture turmoil in the foreign exchange markets and the collapse of ERM I. The dummies $D862$ and $D864$ account devaluations in France and the Netherlands, respectively. As before, the main results of sections 5.2 and 5.3 were invariant to the inclusion of these impulse dummies.

C Appendix: Tests of institutional breaks

In addition to the institutional breaks in s_t^C that were tested and reported in the main text, we also considered several other possible breaks corresponding to various institutional changes believed to have been of importance. Many of these reforms were implemented only gradually but even in cases where reforms were enacted at a particular period, their effects may not have been immediate. For this reason we checked robustness by varying the break dates with a few quarters in each direction. When reform was gradual, we tried every quarter

[47] Since we are modeling $\Delta \boldsymbol{x}_t$ by (4.5), an impulse dummy in $\boldsymbol{d}_t^{\Phi}$ corresponds to a level shift in $\boldsymbol{x}_t$. Similarly, a temporary spike can be modeled by a temporary impulse dummy taking the values one in the relevant quarter and minus one in the consecutive quarter. These dummies are also restricted to be orthogonal to the cointegration space. The orthogonal stochastic trends (long-run conduct) are invariant to the inclusion of these dummy variables.

within the implementation interval. To avoid modeling irrelevant breaks, we only retained break dummies satisfying the criteria that they corresponded to some important institutional event, were significant in the equation for p_t, and could not be long-run excluded in the VAR.

Table C1.1 **Dates and descriptions of the main European institutional reforms during the sample period.**

Event/Country	BE	FR	GE	NL	SP
			Banking reforms*		
Interest rate deregulation	90	90	81	81	92
International capital flows	91	90	< 80	80	92
First banking directive	84–93	< 80	< 80	< 80	86–87
Second banking directive	90–94	92	92	92	92–93
			Other institutional events		
German reunification	–	–	90	–	–
EMU	99	99	99	99	99

* Source: Gual (1999). The sign < indicates that the reform has taken place before our sample period.

The U.S.: In addition to the Riegle-Niel act which was discussed in the main text, we also tested breaks corresponding the Federal Institutions Reform, Recovery, and Enforcement Act (FIRREA) enacted in 1989:3, the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991:4, and the Gramm-Leach-Bliley Act enacted in 1999:4. None of these were found significant by our criteria once the Riegle-Neal act had been accounted for.

Europe: Table C1.1 provides the approximate dates for the main institutional reforms in Europe during the sample period (for a detailed discussion, see Gual, 1999).

As can be seen from the table, the main institutional events were the abolishment of interest rate controls, liberalization of international capital flows, the implementation of the second banking directive, and the introduction of the European monetary union.

Surprisingly, few of these events produced even marginally significant break dummies according to our selection criteria. In the few cases where significant breaks were found, the signs were often opposite to expectation. In fact, most of the significant break dummies correspond to short lived (a few quarters) hikes in the financial spread, and are thus unlikely to be the consequences of institutional reforms. Moreover, none of the significant dummies changed s_t^C nor the main results of Section 5.3, and thus, were excluded these from the analysis.

It may be of particular interest to note that the introduction of EMU did not produce significant breaks in any of the countries (except for a borderline significant positive level shift in the financial spread for the Netherlands). Also, the break dummies for the German reunification were insignificant. However, these results do not necessarily imply that the events were ineffective, only that they were redundant in the empirical model. In other words, the interaction between the variables in the system described by (4.5) was sufficient to capture these institutional effects.

BANK OF FINLAND RESEARCH
DISCUSSION PAPERS

ISSN 0785-3572, print; ISSN 1456-6184, online

Suomen Pankki
Bank of Finland
P.O.Box 160
FI-00101 HELSINKI
Finland

. 2343