The European Consumer: United In Diversity?

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ABSTRACT AND KEYWORDS	
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THE EUROPEAN CONSUMER: UNITED IN DIVERSITY?

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ABSTRACT

The ongoing unification which takes place on the European political scene, along with recent advances in consumer mobility and communication technology, raises the question whether the European Union can be treated as a single market to fully exploit the potential synergy effects from pan-European marketing strategies. Previous research, which mostly used domain-specific segmentation bases, has resulted in mixed conclusions.

In this paper, a more general segmentation base is adopted, as we consider the homogeneity in the European countries' Consumer Confidence Indicators. Moreover, rather than analyzing more traditional static similarity measures, we adopt the concepts of dynamic correlation and cohesion between countries. The short-run fluctuations in consumer confidence are found to be largely country specific. However, a myopic focus on these fluctuations may inspire management to adopt multi-country strategies, foregoing the potential longer-run benefits from more standardized marketing strategies. Indeed, the Consumer Confidence Indicators become much more homogeneous as the planning horizon is extended. However, this homogeneity is found to remain inversely related to the cultural, economic and geographic distances among the various Member States. Hence, pan-regional rather pan-European strategies are called for.

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1. INTRODUCTION

Western-European countries have a longstanding post-WW II tradition of unification, as reflected in agreements to establish the Benelux, the European Free Trade Association, the European Union, and eventually, the European Monetary Union (Tellis, Stremersch, & Yin, 2003; see also McDonald & Dearden, 2005 for an extensive discussion). Also the increasing mobility, education and sophistication of consumers, the growing availability of various distance-spanning technologies, and the emergence of pan-European media have contributed to the perception that distance has become irrelevant within Europe (Mahajan & Muller, 1994; Tellis et al., 2003; ter Hofstede, Steenkamp, & Wedel, 1999). All these factors suggest that the different Member States could be treated as a single market, making a unified, pan-European marketing strategy appropriate (Steenkamp & ter Hofstede, 2002). Such a strategy is attractive not only because of the economies of scale that European standardization may leverage (Yip, 1995), but also by the possibility to coordinate competitive and strategic moves, or to exploit the emergence of global retailers (Özsomer & Simonin, 2004). However, one could also argue that European countries continue to differ considerably from each other, economically (The Economist, 1999), in terms of laws and regulations (The European Voice, 2001), and (some may argue, especially) as far as cultural identity is concerned (Kraus, 2003; Rosenberger, 2004). If countries continue to have predominantly distinct market identities, multi-domestic, rather than pan-European, marketing strategies are called for.

Previous research on the "unity" of the European market has provided mixed evidence. One stream of research supports pan-European marketing strategies. Ter Hofstede et al. (1999), for example, identify a pan-European consumer segment in yoghurt consumption patterns. In Gielens and Dekimpe (2001), neither cultural nor geographical proximity is found to affect the long-run performance of European retailers' international operations. In their study on the drivers of consumer acceptance of new packaged goods, Gielens and Steenkamp (2004) report that various consumer variables work in the same direction in four key European countries (France, Germany, Spain and the United Kingdom),

suggesting that these variables offer a basis for horizontal market segmentation across borders.

Other studies, in contrast, identify substantial differences between various European countries, providing support for multi-domestic or multi-regional strategies. Geographic, economic and/or cultural distances are then found to remain key drivers of market heterogeneity in Europe. Bijmolt, Paas, and Vermunt (2004), for instance, find that European countries differ considerably in financial-product ownership. Based on that dimension, they partition the European market in seven segments. Interestingly, their division is closely linked with geographical proximity. In terms of food culture, Askegaard and Madsen (1998) find Europe to be heterogeneous across its geographical and language borders. In the diffusion literature, Tellis et al. (2003) report substantially different times-to-takeoff for new products in Europe, partially related to cultural distances. Stremersch and Tellis (2004), in turn, discover significant differences in the European growth rates of consumer durables, and find these differences to be mainly related to economic distances. Finally, Kumar, Ganesh, and Echambadi (1998) conclude that geographical, economic and cultural distances help to explain diffusion similarities across Europe.

In sum, research on the unity of the European market offers mixed conclusions. One reason could be that all aforementioned studies consider *domain-specific* segmentation bases (Wedel & Kamakura, 1998), covering specific characteristics as yoghurt consumption, financial-product ownership, or takeoff of consumer durables. While such insights are very useful to the particular industry, they are less likely to generalize to other settings (Steenkamp & ter Hofstede, 2002). We therefore adopt a more *general* measure of consumer homogeneity/heterogeneity in Europe that is less dependent on the specific domain of study. Our point of departure is the Consumer Confidence Indicator (*CCI*) of the various European countries, which has been shown, in a wide variety of settings, to be a useful predictor of consumers' willingness to buy and future expenditures (see e.g. Nahuis & Jansen, 2004). Indeed, the European *CCI* and its US counterpart, the Index of Consumer Sentiment (*ICS*), have been found to be leading indicators of consumer expenditures on durables (Burch &

Gordon, 1984; Throop, 1992), non-durables (Mueller, 1963), household goods and motor vehicles (Friend & Adams, 1964; Adams, 1965), and fashion merchandise (Allenby, Jen, & Leone, 1996), among others. In addition, they have been found to be useful in forecasting recession periods (Batchelor & Dua, 1998), and can be used as a proxy for consumer sunspots, i.e. changes of attitudes (Chauvet & Guo, 2003).

As a consequence, the *CCI* seems an obvious candidate to study in more general terms the extent of homogeneity in consumers' attitudes and buying behavior. The construct also offers some other advantages: these publicly available data are collected *consistently* by the European Commission over *multiple countries* and over a *long time span*. Moreover, as the construct is conceptually similar to the American *ICS*, a formal comparison with the United States, which has a much longer history of unification, becomes feasible.

As a second contribution, we analyze the degree of homogeneity in European consumers' *CCI dynamically*. Previous research is typically based on *static* similarity measures. Bijmolt et al. (2004), for example, partition the European market in terms of a one-shot measure of product ownership; ter Hofstede et al. (1999) segment means-end relations identified in a single data-collection wave; and also Askegaard and Madsen's (1998) analysis of European food cultures is based on lifestyle survey data collected at a single point in time. While international diffusion-based studies consider multiple data points, their main focus lies in subsequently explaining the cross-sectional variation in a single summary statistic, such as the time-to-takeoff (Tellis et al., 2003), average growth rate (Stemersch & Tellis, 2004), or asymptotic value (Gielens & Dekimpe, 2001). However, there is increasing evidence that the relationship between economic variables may vary, in direction and/or importance, over different planning horizons (see e.g. Baxter, 1994). In marketing, numerous studies have demonstrated that the short and long-run effectiveness of marketing-mix expenditures may differ considerably (see e.g. Nijs, Dekimpe, Steenkamp, & Hanssens, 2001; Pauwels, Hanssens, & Siddarth, 2002). Bronnenberg, Mela and Boulding (2004) find that the nature of competitive interactions differs (cooperative versus competitive) for different planning cycles, and Deleersnyder, Dekimpe, & Leeflang (2004) find that the link between aggregate

advertising and GNP over business-cycle frequencies differs from relationships found in the short and long run. Indirect evidence for the relevance of this time dependence in assessing the usefulness of pan-European marketing strategies is provided in the combined studies of Tellis et al. (2003) and Stemersch and Tellis (2004). Using the same European diffusion data, they find different factors (respectively, cultural and economic) to drive the time-to-takeoff and subsequent growth rate of consumer durables. Hence, depending on the planning stage, different country segments emerged.

In this paper, we study how the homogeneity in European *CCI*s varies as the planning horizon is extended. Indeed, country-specific disturbances may dampen the extent of short-run homogeneity, while more homogeneous patterns could come out as the planning horizon is extended. Should this be the case, the feasibility/attractiveness of pan-European marketing strategies will depend on the planning horizon one envisions. A myopic (short-run) focus may then inspire managers to adopt a multi-country strategy, foregoing the potential longer-run benefits of a pan-regional, or even pan-European, strategy.

 To formally investigate this possibility, we apply the *dynamic-correlation* and *cohesion* concepts (Croux, Forni & Reichlin, 2001) to the evolution of the Consumer Confidence Indicators. In so doing, we address the following questions. First, to what extent are the *CCI*s homogeneous across all Member States of the European Union? How does this degree of homogeneity differ across different planning horizons, and how does it compare to the homogeneity across the different regions of the United States? Second, if there is considerable heterogeneity across the Member States, do certain regions (segments) exist which are more homogeneous? Finally, to what extent can geographic, cultural and economic distances help explain the observed heterogeneity, if any, in the various countries' *CCI*?

The remainder of the paper is organized as follows. In Section 2, we formally discuss the concepts of dynamic correlation and cohesion, which are derived in the spectral domain. In Section 3, we discuss the data, and present empirical findings in Section 4. Managerial implications and conclusions are drawn in Section 5.

2. DYNAMIC CORRELATIONS

2.1. *Spectral Analysis*

Most currently available time-series applications in marketing are situated in the time domain (see Dekimpe & Hanssens, 2004 for a recent review). Spectral analysis, situated in the frequency domain and very popular in engineering (see e.g. Priestley, 1981), has received much less attention. Early exceptions are Parsons and Henry (1972), Barksdale, Hilliard and Guffey (1974), and Barksdale, Hilliard and Ahlund (1975). Parsons and Henry (1972) introduced spectral analysis as a diagnostic tool to test the equivalence between actual and predicted sales series. Barksdale et al. (1974) applied spectral tools to study the relationship between advertising expenditures, car factory sales, and new-car registration over different frequencies. Finally, Barksdale et al. (1975) studied the link between price changes and quantities of beef at the slaughter level. Short-run changes in price were found to lead short-run changes in quantity by several months. In contrast, long-run decreases in quantities corresponded to long-run increases in price without time delay.

More recently, Bronnenberg et al. (2004) investigated the nature of competitive price reactions occurring at different frequencies. They found competitors' reactions to short-term price reductions to differ considerably from their reactions to long-run prices changes. In the former case, there was clear evidence of cooperative behavior between brands (i.e. the reactions are negatively correlated), while competitive behavior prevailed in the longer run (i.e. the correlation is positive). Finally, Deleersnyder, Dekimpe, Sarvary, and Parker (2004) used spectral band-pass filters in their study on the link between the durables' diffusion patterns and business-cycle fluctuations.

A common finding in the above studies is that marketing relationships may differ across different frequencies (planning horizons). This led Pauwels et al. (2004) to call for more spectral-based time-series applications in marketing, as this could lead to novel insights into a wide variety of substantive marketing problems.

Central to spectral theory is the notion that any time series can be decomposed into an infinite sum of (uncorrelated) cyclical components, each having a different frequency λ. Each frequency λ (ranging between 0 and π) corresponds to a unique time horizon T, with $T = (2\pi/\lambda)$. In case of monthly data, a frequency of 0.5 represents a one-year time horizon, the yearly cyclical component in the time series. The underlying intuition is illustrated in Figure 1 for two simulated processes.[2] Both series are formed by higher-frequency components (corresponding to shorter-run time horizons), middle-frequency components (for middle-run time horizons), and lower-frequency components (for longer-run time horizons). All components are added to each other to compose the time series, as illustrated in the final plot of Figure 1.

[INSERT FIGURE 1 ABOUT HERE]

In reality, a time series is composed of an infinite sum of such components, which can be isolated through spectral analysis. This makes it possible to study the correlation between two time series at any time horizon. In Figure 1, we see that the high-frequency components ($\lambda = 1.57$; $T = 4$ months) are quite uncorrelated, having different amplitudes and being out-of-phase.[3] On the contrary, the low-frequency components ($\lambda = 0.26$; $T = 24$ months) are almost perfectly correlated, as their amplitudes are very close and their signals are in phase.

Let us now consider N stationary time series $x_1,...,x_N$ of length T. In our application, the series represent the (first-differenced) *CCI* of the various EU countries. Traditional unit-root tests can be used to test for the stationarity of the various series (see e.g. Pauwels et al., 2002, or Nijs et al., 2001, for recent marketing applications). Removal of stochastic trends – by first differencing the series – is called for, as this trend would otherwise be treated as part of a very long oscillation, which would swamp the effects of shorter-period data (Parsons and Henry, 1972). Each stationary series x_i is characterized by a spectral density function, or spectrum $S_{x_i}(\lambda)$, which is defined at each frequency $\lambda \in [0, \pi]$ by:

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[2] The time series have been simulated over 50 months. The first plot represents high-frequency components (about 4 months), the second medium-frequency components (12 months), and the third low-frequency components (24 months).
[3] The *amplitude* of the cyclical components is given by the height of the waves. Waves having the same frequency but with their maxima occurring at different instances are said to be *out-of-phase*.

$$S_{x_i}(\lambda) = \frac{1}{\pi} \sum_{k=-\infty}^{+\infty} \gamma_{x_i}(k) \, e^{-i\lambda k} \qquad (1)$$

with $\gamma_{x_i}(k) = Cov(x_{i,t}, x_{i,t-k})$, the autocovariance of x_i at lag k. The spectrum $S_{x_i}(\lambda)$ measures the variance of the cyclical component at frequency λ of the time series x_i.[4] In turn, the cross-spectrum $S_{x_i x_j}(\lambda)$ characterizes the relationship between two time-series x_i and x_j at frequency λ:

$$S_{x_i x_j}(\lambda) = \frac{1}{\pi} \sum_{k=-\infty}^{+\infty} \gamma_{x_i x_j}(k) \, e^{-i\lambda k} = C_{x_i x_j}(\lambda) + i \, Q_{x_i x_j}(\lambda) \qquad (2)$$

where $C_{x_i x_j}(\lambda)$ is the real part of the cross-spectrum and $Q_{x_i x_j}(\lambda)$ the imaginary part. Here $\gamma_{x_i x_j}(k) = Cov(x_{i,t}, x_{j,t-k})$ represents the cross-covariance between $x_{i,t}$ and $x_{j,t}$ at lag k. Conceptually, $S_{x_i x_j}(\lambda)$ is a measure of the covariance between the cyclical components corresponding to the frequency λ of the time series $x_{i,t}$ and $x_{j,t}$. The spectra are estimated by computing first the discrete Fourier transform of the time series. The squared modulus of this transform is then smoothed by a weighted moving average,[5] yielding the estimated spectrum. A detailed treatment on the spectral analysis of time series can be found in Koopmans (1995), or Brockwell and Davis (2002).

2.2. *Dynamic Correlation*

The spectral-based *dynamic correlation* first discussed in Croux et al. (2001)[6] provides a formal measure of the correlation, or degree of comovement, between two series x_i and x_j at each individual frequency λ, and is given by

$$\rho_{x_i x_j}(\lambda) = \frac{C_{x_i x_j}(\lambda)}{\sqrt{S_{x_i}(\lambda) S_{x_j}(\lambda)}}. \qquad (3)$$

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[4] The variance of a time series equals the total area underneath the spectrum. In other words, the spectrum shows the distribution of the total variance across the frequency band (Chatfield, 1996, p.96).
[5] In our empirical application, we will apply three times the Daniell's smoother. Practically, the spectral analysis was performed using build-in routines of the S-Plus statistical software package.
[6] Other applications of the concept include Sussmuth and Woitek (2004) and Carlino and DeFina (2004).

This correlation, which ranges between -1 and +1, is conceptually similar to the correlation between two series in the time domain. The higher its value, the more similar the fluctuations at that frequency are. However, unlike the (single) static correlation in the time domain, one now obtains a correlation coefficient that can vary across different frequencies or planning horizons. Note that prior marketing studies have used the cointegration concept to describe the long-run comovement between time series (see e.g. Franses, Kloek, & Lucas, 1999, or Srinivasan, Popkowski Leszczyc, & Bass, 2000). In so doing, one focuses on the dynamic correlation at frequency zero between the first-differentiated time series, which equals one (in absolute value) when both original series are cointegrated.[7] Our dynamic correlation concept is more comprehensive in that we look at the correlation across the entire frequency band, and not only at the zero frequency. As discussed before, the planning horizon is inversely related to the frequency. Hence, the higher (lower) the frequency, the shorter (longer) the planning horizon.

[INSERT FIGURE 2 ABOUT HERE]

Figure 2 depicts graphically the dynamic correlation between the aforementioned two simulated series. In line with our discussion on Figure 1, the lowest frequencies show the highest correlation, implying that the longer-run fluctuations in the series are strongly related, i.e. show quite similar patterns. The higher frequencies correspond with a much lower correlation, implying that both series are characterized by much more idiosyncratic short-run fluctuations. Obviously, this dynamic correlation pattern is more insightful than the single static correlation coefficient of 0.293 between both simulated series.

2.3.   Cohesion and Cross-Cohesion

From a panel of *N* time series, we may derive *N*(*N*-1)*/2* possible pair-wise dynamic correlations. The higher these correlations, the more homogeneous the respective countries are, in that their customers react in a similar way to various market disturbances.

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[7] The relation between cointegration and the dynamic correlation is discussed more formally in Croux et al. (2001).

To obtain an aggregate measure of comovement within this panel, or part of it, we can compute the *cohesion* (Croux et al., 2001) at frequency λ denoted by $Coh(\lambda)$. For $1 \le n_1 \le N$ series, this cohesion is obtained as:

$$Coh(\lambda) = \frac{2}{n_1(n_1 - 1)} \sum_{i,j,i<j}^{n_1} \rho_{x_i x_j}(\lambda).$$
(4)

Considering our entire set of European countries ($n_1 = N$), one can thus derive an aggregate measure of European homogeneity. Alternatively, considering smaller subsets of countries ($n_1 < N$), one can assess the cohesion within a priori-defined country segments. In line with Tellis et al. (2001), one could, for instance, assess to what extent the Scandinavian, Mediterranean and Midwest segments are more homogeneous (i.e. have a higher cohesion) than Europe as a whole, and if so, at what frequencies (planning horizons).

Apart from an aggregate measure of cohesion *within* a set of time series, one could also derive a measure of the cohesion *between* two distinct groups of time series. To that extent, one can aggregate the dynamic correlations into a *cross-cohesion* index at frequency λ,

$$Cross - Coh(\lambda) = \frac{1}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \rho_{x_i x_j}(\lambda),$$
(5)

representing the comovement between two distinct subsets of size n_1 and n_2. In our specific setting, one could, for example, derive the cross-cohesion between the European countries and the United States, to assess whether the evolution in the European countries' *CCI* is in sync with the evolution in the American *ICS*.

The cohesion offers an aggregate measure of European homogeneity. However, there may be quite some variability between the different pair-wise dynamic correlations, which raises the question what factors drive the extent of correlation between two countries' *CCI*. As such, one can assess whether a larger economic, geographic and/or cultural distance significantly decreases the resulting homogeneity in the respective countries' *CCI*. This analysis can be implemented for specific frequencies, in which case the $N(N-1)/2$ dynamic correlations at a given frequency could be regressed against the different distance measures.

Alternatively, one could aggregate the dynamic correlations in (3) across a pre-specified frequency band $\Lambda = [\lambda_1, \lambda_2[$, for $0 \leq \lambda_1 < \lambda_2 \leq \pi$, as

$$\rho_{x_i x_j}(\Lambda) = \int_{\lambda_1}^{\lambda_2} \rho_{x_i x_j}(\lambda) \, \mathrm{d}\lambda . \qquad (6)$$

As the frequencies are inversely related to the planning horizon (see before), this procedure allows one to make inferences on the extent of European homogeneity across the short, medium and long run. The latter approach is conceptually similar to Deleersnyder et al. (2004), in that they also consider jointly all frequencies in a certain frequency band (in their case, all frequencies corresponding to planning horizons between two and eight years), and is less sensitive to the specific frequency one has selected.

3. DATA

We consider the Consumer Confidence Indicator in fourteen European countries, namely Austria (AU), Belgium (BE), Denmark (DK), Finland (FI), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Portugal (PO), Spain (SP), Sweden (SE), The Netherlands (NL), and the United Kingdom (UK). Luxembourg is not included, as no data were collected for this country before 2002. The *CCI* is derived through consumer surveys collected by the European Commission and its Member States in the framework of the Joint Harmonised EU Programme. Each month, over 30,000 consumers are surveyed, and the *CCI* is computed as the arithmetic average of the balances (in percentage points) of answers pertaining to the financial situation of the households ("How do you expect the financial position of your household to change over the next twelve months?"), the general economic situation ("How do you expect the general economic situation in this country to develop over the next twelve months?"), savings ("Over the next twelve months, how likely is it that you save any money?"), and (with inverted sign) unemployment expectations ("How do you expect the number of people unemployed in this country to change over the next twelve months?"). Respondents are asked whether they expect the variables of interest to increase, decrease, or remain stable over time. The decreases (in percentage points) are subsequently

subtracted from the increases to obtain balance figures. A directional questionnaire is used as directional changes have been found to be easier to predict than point values (Jonung, 1986). These balance data are seasonally adjusted by the data provider. Details on the derivation of the *CCI* are provided on the website of the Directorate General Economy and Finance (DG ECFIN) of the European Commission.[8] Previous research on the *CCI* includes Vanden Abeele (1983), Praet and Vuchelen (1989), Batchelor and Dua (1998), and Golinelli and Parigi (2004), among others. Our series span the period from November 1995, the entry date of Austria, Finland and Sweden into the European Union, until February 2004, resulting in 100 data points. The various *CCI* time series are depicted in Appendix A.

To allow for a formal comparison with the United States, we also obtained information on the American *ICS* over the same time span. Following the pioneering work of Katona (1951, 1979), the *ICS* has been used in numerous marketing studies, such as Allenby et al. (1996), Kamakura and Gessner (1986) and Kumar, Leone, and Gaskins (1995), among others, and is conceptually similar to the European *CCI*.[9] In line with Croux et al. (2001), we consider four regions within the US: North-East, Midwest, South and West.

Finally, to study the cross-sectional variation in the pair-wise dynamic correlations, we introduce various distance measures. The *geographic* distance between two countries i and j (GEO_{ij}) is measured as the shortest distance (in hundred kms) between both capitals. In line with Mitra and Golder (2002), the *economic* distance between two countries is based on four dimensions, i.e. the difference in the countries' economic size (reflected in their Gross Domestic Product, *GDP*), economic prosperity (measured through their Gross Domestic Product per Capita, *GDPC*), economic infrastructure (as reflected in the number of kilometers of railroad per square km, *RAIL*), and economic accessibility (operationalized through their population density, *DENS*). The economic distance between two countries on a given dimension is defined as the absolute value of the difference between their log-transformed score on that dimension. For example, the economic-size distance is measured as $|\log(GDP_i)$

$– \log(GDP_j)\big|$. Relevant data were obtained from the World Factbook 2004.[10] To conceptualize the *cultural* distances, we use the Schwartz national-culture framework (see e.g. Schwartz, 1994; Schwartz & Ros, 1995), which has emerged as a major refinement and alternative to Hofstede's values (Steenkamp, 2001). Schwartz's framework is more recent and is based on consumer – rather than organizational – values (Steenkamp, ter Hofstede, & Wedel, 1999) which render it more applicable to the context of our study. Cultural distance is defined in terms of the seven dimensions: conservatism *(CONS)*, intellectual autonomy (*INTEL*), affective autonomy (*AFFECT*), hierarchy (*HIER*), egalitarianism (*EGAL*), harmony (*HARM*), and mastery (*MAST*). The distance on each cultural dimension is obtained as the absolute difference between two countries' score on a given dimension. Cultural data, reported in Schwartz and Ros, are available for eleven countries. As such, the regressions in Section 4.4 are implemented on 55 (= (11x10)/2) observations. All distance measures are time-invariant, as they are either intrinsically constant (geographic distance), not available as time-varying variable (cultural distance), or only collected at a higher level of temporal aggregation (economic distances) than the monthly *CCI* or *ICS*.

4. RESULTS

The 14 European *CCI* series result in 91 possible dynamic correlations. For illustrative purposes, we present in Section 4.1 the dynamic correlation between three key European countries: France, Germany and the United Kingdom. Next, we derive an aggregate measure for the degree of homogeneity across the different Member States through the cohesion index (Section 4.2), and compare this measure with (i) the cohesion in *ICS* across the four US regions, and (ii) the cross-cohesion between the US and the European Union (Section 4.3). We subsequently assess whether there are certain clusters of countries which, among themselves, are relatively more homogeneous than the Union as a whole. Finally, in Section 4.4, we assess whether the observed variability between the pair-wise dynamic correlations is driven by the geographic, economic and/or cultural distance(s) between the respective countries, and how this relative importance varies across different planning horizons.

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[10]Available on the website of the CIA, http://www.cia.gov/cia/publications/factbook/.

4.1. Pair-Wise Dynamic Correlations

Rather than presenting all 91 dynamic correlations (which are available from the authors upon request), we focus on the dynamic correlations between the *CCI* of three key countries: France, Germany and the United Kingdom. France and Germany are often seen as two key forces (both economically and politically) of the European Unification (The Economist, 2003). The United Kingdom, in contrast, while also being an important player, has been argued to have a rather distinct position, not only geographically, but also in terms of economic integration and culture (Nothcott, 1995).

In line with Jansen and Nahuis (2003), preliminary unit-root tests found the different *CCI* series to be integrated of order one.[11] The dynamic correlations were therefore computed on the first differences. For notational simplicity, we still refer to these first-differenced series as *CCI*s. The corresponding dynamic correlations are presented in Figure 3. On the bottom horizontal axis, we depict the frequency in radians, while the top axis presents the corresponding planning horizon (in months). As indicated before, the higher the frequency, the lower the planning horizon. In all instances, the short-run dynamic correlation (corresponding with the higher frequencies) is close to zero. This suggests that many of the disturbances that drive the high-frequency (monthly, bimonthly, etc) fluctuations in consumer confidence are country specific, and not correlated across the respective countries. This short-run heterogeneity supports the idea of multi-domestic strategies. However, especially in the case of France and Germany, this may be an overly myopic view, in that the dynamic correlation increases considerably as the planning horizon is extended beyond six months. Market shocks that drive the longer-evolution in consumers' confidence therefore have a similar impact in both countries, which supports a more integrated approach across these two countries. The dynamic correlations with the United Kingdom, in contrast, remain considerably smaller at all frequencies. These findings, based on consumer perceptions, are in line with earlier research by Lemmens, Croux, and Dekimpe (2005). In their pan-European study on the predictive content of managers' production expectations, they found significant

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[11] Results are available from the authors upon request.

cross-border effects between France and Germany, while the UK occupied a fairly isolated position.

[INSERT FIGURE 3 ABOUT HERE]

While one should be careful when generalizing from a limited number of cases, the above discussion already suggests that there is little homogeneity in the short-run fluctuations in consumers' confidence. In terms of the longer-run movements, in contrast, there seems to be more variability across country pairs, and a potential to identify relatively homogeneous subsets. Finally, the observed differences seem to be related to the relative "closeness" of the different countries. Next, we investigate more formally these preliminary patterns.

4.2. *The European Cohesion in Consumer Confidence*

The first set of observations is confirmed in the European cohesion measure, which aggregates all 91 pair-wise correlations. As indicated in Figure 4, the European cohesion is very low at the high frequencies, suggesting very little pan-European homogeneity in the short-run fluctuations in consumer confidence across the different Member States. This implies that either country-specific shocks (local unemployment figures, the outcome of local elections, etc) drive these short-run fluctuations, or that different countries have different short-run reactions to common shocks (s.a. news issued by the European Central Bank, world events, etc). Illustrating the former case, the closure of Renault's Belgian factory, announced in February 1997 (The Economist, 1997), caused a sharp fall in the Belgian *CCI* of 7 points, while most other countries were unaffected. The common shock of September 11, 2001 in turn, affected the confidence in all Member States considerably, but some countries (e.g. the British and Irish *CCI*s lost 7 points over the month) to a much larger extent than others (e.g. the Nordic countries lost less than 2 points).[12]

[INSERT FIGURE 4 ABOUT HERE]

In line with the patterns observed for France and Germany, we further see that the cohesion increases somewhat as the planning horizon is extended, indicating a more

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[12] More details can be found in the "Employment in Europe 2001, Autumn Update" report of the European Commission, DG Employment and Social Affairs.

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homogenous evolution once the dust has settled. To put the European cohesion levels in perspective, we compute as benchmark the cohesion in the *ICS* across the four US regions.[13] A priori, we expect the latter cohesion to be considerably higher, if only because the United States have a much longer history of unification while also sharing a common language and currency, and having a single foreign policy and army. Across the entire range of frequencies, the US-based cohesion indeed exceeds its European counterpart. Interestingly, at the higher frequencies, we see that also within the United States, there remains considerable heterogeneity in the behavior of the *ICS*. This finding is in line with the work of Wells and Reynolds (1979) and Hawkins, Roupe and Coney (1981) who found significant geographical variation in consumer values, attitudes and consumption across different regions of the United States, and of Mittal, Kamakura and Govind (2004), who found such differences in consumers' satisfaction with car dealers. However, because of the cross-sectional nature of their data, the increasing homogeneity over longer time horizons could not be inferred from these earlier studies.

When looking at the cross-cohesion between Europe and the different US regions, we find a comparable pattern, with higher correlations at lower frequencies. As the planning horizon is extended, the European *CCI* and the American *ICS* increasingly react in similar ways. While this may not seem too surprising, given the United States' economic and political power in today's global marketplace (Julius, 2005), it is interesting to note that the cohesion within Europe does not exceed the cross-cohesion level for planning horizons beyond four months. Hence, recent political claims on Europe's distinct (relative to the US) identity are not yet fully reflected in its consumers' perceptions.

4.3.   European Segments

As the overall cohesion across all 14 countries is fairly small, even at the lower frequencies, the question emerges whether this picture changes when considering smaller subsets of countries. Indeed, a few discrepant countries may well drive the overall homogeneity estimate down. Looking at Figures 2 and 3, it is obvious that the European-

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[13] The absence of *ICS* data at the state level precludes the derivation of a (cross-) cohesion measure for the 52 States of America.

based cohesion is considerably lower than the dynamic correlations reported between France and Germany. While one could adopt several a priori segmentation schemes, we identified, for illustrative purposes, the following three segments: (i) the Scandinavian (DK, FI, and SE), (ii) Mediterranean (GR, IT, PO, SP), and (iii) Midwest countries (AU, BE, DE, FR, NL). Apart from France (which they classify as a Mediterranean country), this typology closely follows the one adopted in Tellis et al. (2003).

[INSERT FIGURE 5 ABOUT HERE]

As indicated in Figure 5, especially the Scandinavian and Midwest countries are characterized by a considerably higher homogeneity at the lower frequencies. As for the former, their cohesion at longer planning horizons even approaches the values obtained within the United States. The emergence of a homogeneous Scandinavian segment confirms previous findings of Kumar et al. (1998), Helsen, Jedidi, and DeSarbo (1993) and Tellis et al. (2003). Much less homogeneity is observed among the Mediterranean countries, irrespective of the time horizon considered. These findings are in line with Bijmolt et al. (2004) who, in their study on financial-product ownership, identified relatively homogenous segments among respectively, the Nordic and Midwest countries, while most Mediterranean countries formed single-country segments.

4.4.   Does Distance Still Matter?

The examples in Figure 3 (for France, Germany and the UK) suggested that there may be quite some variability in dynamic correlation both across different country pairs, and across different time horizons. To more formally assess this variability, we regress the pair-wise correlations across various indicators of economic, geographic and cultural distance, for three different planning horizons, i.e. the short, medium and longer run.

In the marketing literature, no unique definition exists as to what constitutes the short, medium and long run (see in this respect the very different operationalizations advocated in Dekimpe & Hanssens, 1999, and Mela, Gupta, & Lehmann, 1997). As it has been found that consumers' attitudes change quickly (Leone & Kamakura, 1983), causing them to sometimes use very short (even monthly) planning horizons (Thaler, 1985), we define our short-run

planning horizon as those fluctuations with a periodicity inferior to four months. This

corresponds to a frequency band $\Lambda_1 = \left[\dfrac{\pi}{2}, \pi\right[$. The medium term is assumed to correspond to

a planning horizon of four to twelve months, with frequency band $\Lambda_2 = \left[\dfrac{\pi}{6}, \dfrac{\pi}{2}\right[$, while the

longer-term fluctuations are assumed to correspond with cycles of twelve months to two

years, i.e. frequency band $\Lambda_3 = \left[\dfrac{\pi}{12}, \dfrac{\pi}{6}\right[$. We do not take fluctuations of higher periodicity

into account to ensure a sufficient number of cycles for reliable analysis.[14] As indicated in

Section 2.3, we integrate the dynamic correlations across the different frequencies in a given

frequency band to arrive at a single (average) estimate for the dynamic correlation in that

band. Three regression models are subsequently estimated, with the dynamic correlation in,

respectively, the short, medium and long-run frequency band as dependent variable, and the

various indicators for geographic (*GEO*), economic (*GDP*, *GDPC*, *DEN*, *RAIL*) and cultural

(*CONS*, *HIER*, *AFFEC*, *INTEL*, *MAST*, *EGAL*, *HARM*) distance as explanatory variables.

Single-equation estimation techniques are used. A system's approach would not result in

more efficient parameter estimates, as all equations contain the same set of explanatory

variables. Preliminary White tests (available upon request) do not reveal significant

heteroskedasticity in any of the regressions. As each observation in the regressions

corresponds to a pair of countries, possible correlation among the error terms can be modelled

by introducing random country effects, as in Sethuraman, Srinivasan, and Kim (1999). The

latter, however, turned out not to be important.[15] Hence, we preferred to stick to the OLS

estimator. Finally, as there may be multicollinearity between the different indicators of

economic (cultural) distance, we focus on the more robust joint *p*-values. These are reported

in Table 1. The individual coefficient estimates can be found in Appendix B.

[INSERT TABLE 1 ABOUT HERE]

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[14] We still observe four cycles of two years in our sample.
[15] Farley and Lehmann (1986) note in this respect that the bias due to non-independence may not be serious if the percentage of non-zero correlations between pairs of error terms is relatively small. In our application, this ratio is about 15%. When adopting a GLS approach to account for the aforementioned dependencies, qualitatively similar conclusions were indeed obtained (detailed results available upon request).

Remember that in terms of the short-run correlations, very small values were obtained for each of the three country pairs of Figure 3. This pattern was also found in the larger set of correlations. Not surprisingly, the short-run regression results in a very low R^2 (0.20), and an insignificant overall F-statistics ($p= 0.60$). Irrespective of the geographic, economic or cultural distance, the high-frequency fluctuations in two countries' *CCI* do not show much correlation.

As one moves to the lower-frequency movements in *CCI*s, the explanatory power of the cross-sectional regressions increases. In the medium run, the R^2 increases to 0.46, and becomes 0.60 in the long run. Also the corresponding F-statistics become highly significant ($p<0.004$ and 0.000, respectively). In the medium run, the economic distance becomes significant[16] ($p<0.05$), while in the long run, all three distance components become significant. In terms of the individual variables, the correlation in longer-run *CCI* movements decreases as the geographic distance increases ($p<0.10$), as the absolute difference in the countries' GDP ($p<0.05$) and GDP per capita ($p<0.10$) becomes larger, and as they become more culturally different on the hierarchy ($p<0.10$), egalitarianism ($p<0.01$) and harmony ($p<0.01$) dimensions. No such insights could have been obtained from the traditional static correlations, as this resulted in a poorly fitting ($R^2 = 0.17$) and insignificant (p-value of the overall *F*-statistics = 0.71) relationship.

5. CONCLUSIONS

The ongoing unification which takes place on the European political scene, along with recent advances in consumer mobility and communication technology, raises the question whether the different Member States of the European Union can be treated as a single market to take full advantage of pan-European marketing strategies. However, *distance remains an important determinant* of (dis)similarities in European consumers' confidence. Recent claims on the "death of distance" (The Economist, 1995) are therefore premature.

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[16] This result is driven by the GDP variable ($p < 0.05$). The negative sign of the associated parameter indicates less similarity in *CCI* movements as the economic distance increases.

Our analyses clearly indicate that the European Union does not yet constitute a single, homogeneous, market. Not only are the short-run (high-frequency) movements in consumers' confidence driven by country-specific shocks and/or differing reactions to common shocks, but also the homogeneity in their longer-run reactions decreases significantly as the distance between the different European countries increases. As such, in terms of short-term tactical marketing decision making, country-specific strategies may still be called for. For more strategic decisions that have longer-run implications, there is more cross-country homogeneity to exploit, but the continued significance of geographic, economic and cultural distances suggests more potential for pan-regional strategies than for a single pan-European strategy.

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Figure 1: The decomposition of two time series in their components at different frequencies
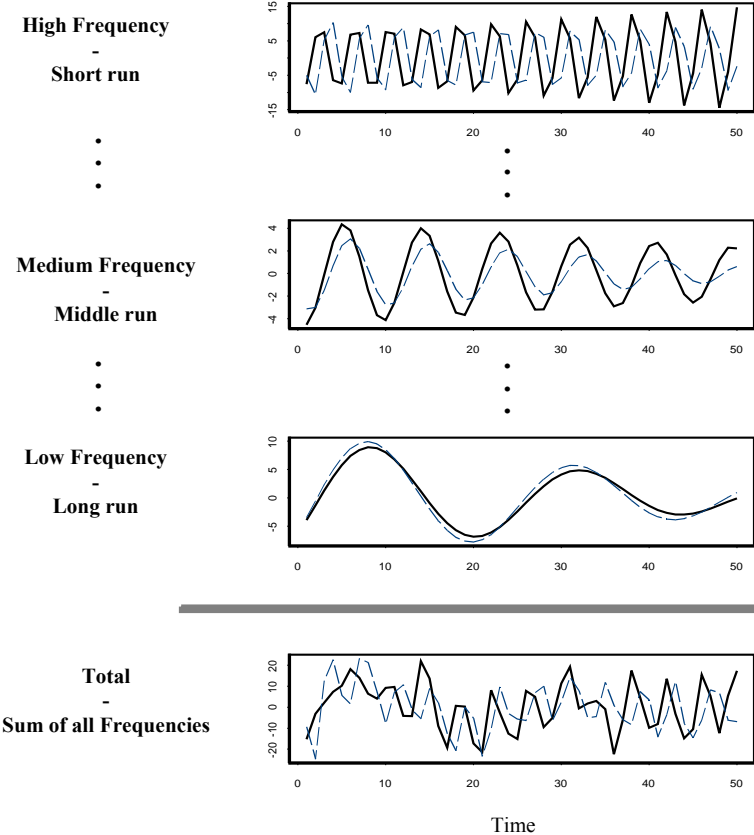

High Frequency
-
Short run

Medium Frequency
-
Middle run

Low Frequency
-
Long run

Total
-
Sum of all Frequencies

Time

Figure 2: The dynamic correlation between the simulated series of Figure 1

Planning Horizon (in Months)

31.4 15.7 10.4 7.8 6.2 5.2 4.4 3.9 3.4 3.1 2.8 2.6 2.4 2.2 2 1.9

Dynamic Correlation

Frequency
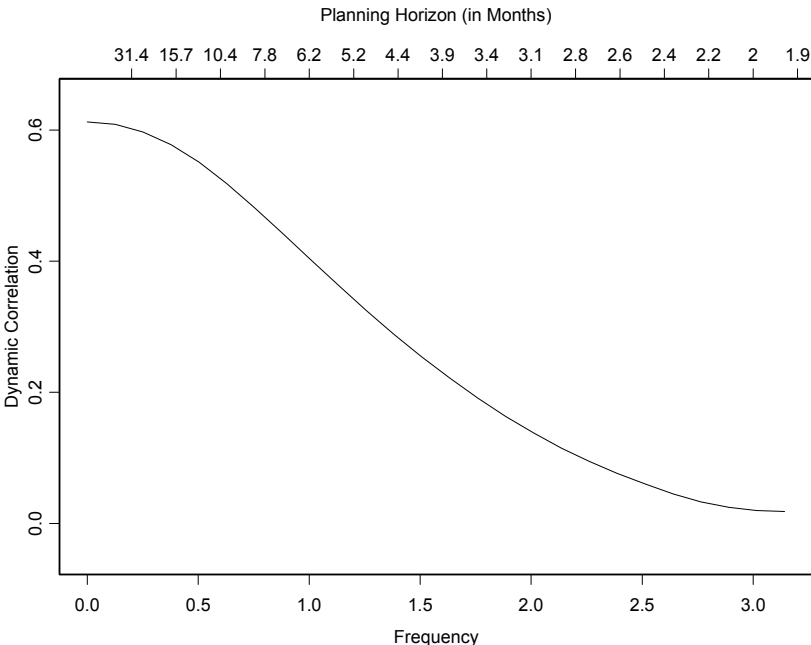
Figure 3: Dynamic correlation for France, Germany and the United Kingdom.
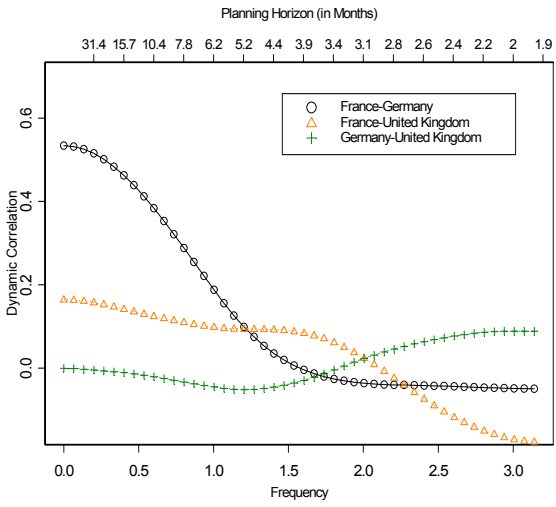

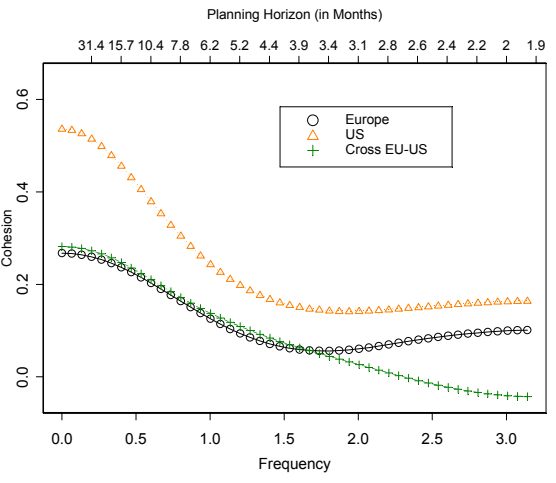**Figure 4: Cohesion and cross-cohesion within and between Europe and the United States.**

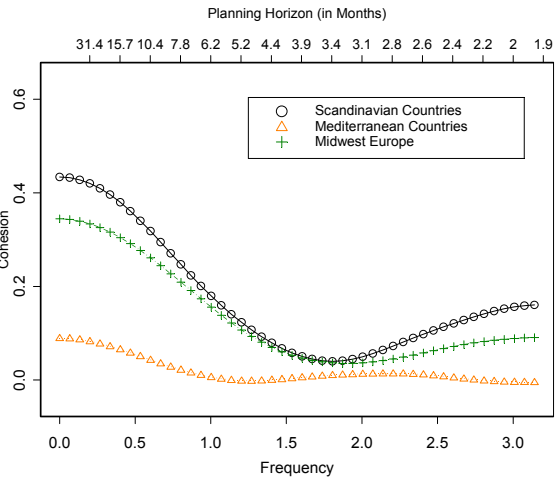**Figure 5: The cohesion index within predefined market segments**

Table 1: OLS-estimated joint *p*-values, F-statistics and R² measures for different time horizons.

	Static correlation	Short run	Middle run	Long run
Joint p-values				
Geographic distance	0.168	0.595	0.311	0.098
Economic distance	0.568	0.471	0.014	0.005
Cultural distance	0.924	0.454	0.170	0.006
Overall F-statistics, p-value	0.713	0.595	0.004	0.000
R-squared	0.173	0.196	0.460	0.595

APPENDIX A: The evolution of the *CCI*s in Europe.
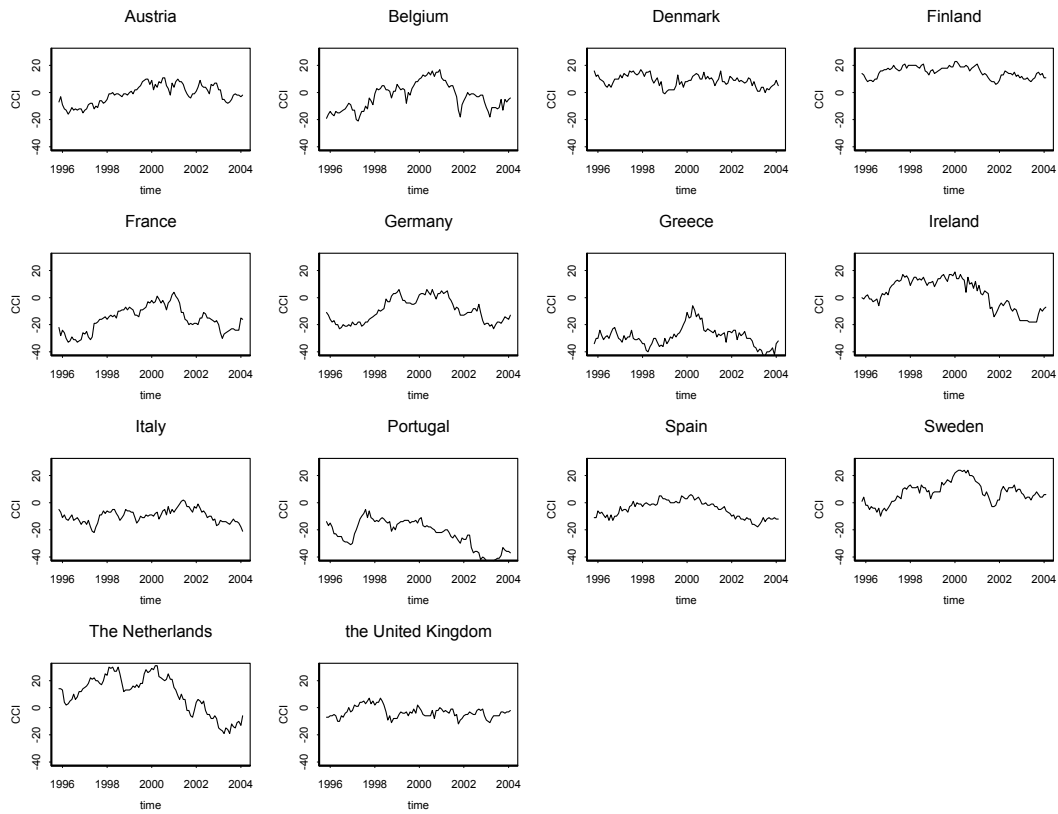
APPENDIX B: OLS-estimated regression coefficients (and their standard errors) of the drivers of variability among the dynamic correlations for different time horizons.

	Static correlation	Short run	Middle run	Long run
Geographical distance				
GEO	-0.004	-0.002	-0.003	-0.006*
	(0.003)	(0.004)	(0.003)	(0.004)
Economic distances				
GDP	-0.004	0.023	-0.056**	-0.076**
	(0.023)	(0.030)	(0.025)	(0.030)
GDPC	-0.022	0.143	-0.237	-0.344*
	(0.149)	(0.198)	(0.165)	(0.198)
DEN	0.033	0.047	0.035	0.043
	(0.025)	(0.033)	(0.027)	(0.033)
RAIL	-0.021	-0.089*	0.033	0.040
	(0.038)	(0.050)	(0.042)	(0.050)
Joint test p-value	0.568	0.471	0.014**	0.005***
Cultural distances				
CONS	-0.086	0.013	-0.110	-0.149
	(0.153)	(0.205)	(0.171)	(0.205)
HIER	-0.062	0.040	-0.135	-0.345*
	(0.133)	(0.177)	(0.148)	(0.177)
AFFEC	0.098	0.164	0.086	-0.063
	(0.079)	(0.106)	(0.088)	(0.106)
INTEL	0.013	-0.074	0.052	0.110
	(0.071)	(0.095)	(0.079)	(0.095)
MAST	-0.003	-0.044	-0.021	-0.055
	(0.098)	(0.130)	(0.108)	(0.130)
EGAL	-0.112	0.372	-0.463**	-0.707***
	(0.168)	(0.224)	(0.187)	(0.224)
HARM	-0.075	0.077	-0.218*	-0.400***
	(0.099)	(0.132)	(0.110)	(0.132)
Joint test p-value	0.924	0.454	0.170	0.006***
Intercept	0.168**	-0.040	0.321***	0.676***
	(0.071)	(0.094)	(0.079)	(0.094)
n =55				
Overall F-statistics, p-value	0.713	0.595	0.004***	0.000***
R-squared	0.173	0.196	0.460	0.595

* p<0.100; ** p<0.050; *** p<0.010

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