Kiel Working Papers

Kiel Institute for the World Economy

# The Euro's Trade Effect under Cross-Sectional Heterogeneity and Stochastic Resistance

by Helmut Herwartz and Henning Weber

**No. 1631**| June 2010

Web: www.ifw-kiel.de

Kiel Working Paper No. 1631 | June 2010

# The Euro’s Trade Effect under Cross-Sectional Heterogeneity and Stochastic Resistance

Helmut Herwartz and Henning Weber

Abstract:
This paper investigates if the euro's effect on euro-area trade differs across trade sectors and across country pairs, and to what degree heterogeneity matters for estimating the aggregate euro effect. Time-varying latent variables, which are specific to each sector in each country pair, control for omitted trade costs and mismeasured resistance terms. Parameter heterogeneity and time-varying latent variables are both strongly supported by the data. Due to decreasing trade costs, aggregate exports within the euro area increase between 2000 and 2002 by 15 to 25 percent compared with aggregate exports between European economies which are not members of the euro area. Adjustment within individual sectors is rapid whereas aggregate adjustment is more spread out and gradual since different sectors adjust at distinct times.

Keywords: Euro's trade effect, parameter heterogeneity, smooth-transition model.

JEL classification: C31, C33, F13, F15, F33, F42

Kiel Institute for the World Economy
24105 Kiel, Germany

**Helmut Herwartz**
Telephone: +49 431 880 1423
E-mail: h.herwartz@statecon.uni-kiel.de

**Henning Weber**
Telephone: +49 431 8814 572
E-mail: henning.weber@ifw-kiel.de

# The Euro's Trade Effect under Cross-Sectional Heterogeneity and Stochastic Resistance

Helmut Herwartz* and Henning Weber†

June 15, 2010

**Abstract**

This paper investigates if the euro's effect on euro-area trade differs across trade sectors and across country pairs, and to what degree heterogeneity matters for estimating the aggregate euro effect. Time-varying latent variables, which are specific to each sector in each country pair, control for omitted trade costs and mismeasured resistance terms. Parameter heterogeneity and time-varying latent variables are both strongly supported by the data. Due to decreasing trade costs, aggregate exports within the euro area increase between 2000 and 2002 by 15 to 25 percent compared with aggregate exports between European economies which are not members of the euro area. Adjustment within individual sectors is rapid whereas aggregate adjustment is more spread out and gradual since different sectors adjust at distinct times.

JEL Code: C31, C33, F13, F15, F33, F42

Keywords: Euro's trade effect, parameter heterogeneity, smooth-transition model

*Christian-Albrechts-University at Kiel, Institute of Statistics and Econometrics, Ohlshausenstr. 40, D - 24098 Kiel, Germany, and Kiel Institute for the World Economy, Hindenburgufer 66, D - 24105 Kiel, Germany, h.herwartz@stat-econ.uni-kiel.de, Tel.: +49 (431) 880 1423.

†Kiel Institute for the World Economy, Hindenburgufer 66, D - 24105 Kiel, Germany, henning.weber@ifw-kiel.de, Tel.: +49 (431) 8814 572.

# 1 Introduction

A core argument in favor of the common European currency is that the euro stimulates trade within the euro area by permanently reducing trade costs. Many studies analyze whether or not trade costs within the euro area actually fall with the introduction of the euro. However, most of these studies impose a homogenous impact of trade costs across trade sectors and across country pairs. The purpose of this study is to investigate if permanent changes in trade (costs) around the introduction of the euro differ across sectors and across country pairs, and to what degree heterogeneity matters for estimating the adjustment path of aggregate trade to the euro.

Heterogeneous impacts of trade costs on trade allow one to decompose adjustment of aggregate euro-area trade into adjustment of individual trade sectors in different country pairs. Decomposing aggregate into individual adjustment may deliver insights into which aspect of individual adjustment survives into aggregate adjustment and which aspect of individual adjustment is blurred through aggregation. In contrast, imposing a homogeneous impact of trade costs on trade across sectors and country pairs might lead one to overlook considerable and informative differences between aggregate and individual adjustment. Furthermore, economic reasoning indicates an important role for heterogeneity in the adjustment paths to a common currency (Anderson and van Wincoop (2004)). Countries are more or less open to trade and differ in how much they trade within and outside the euro-area. Heterogeneity regarding openness to trade and the set of trading partners suggests that national trade responds differently to changes in trade costs. Similarly, trade sectors are most likely to differ in their extent of vertical differentiation, the magnitude of economies of scale, the degree of industrial concentration, the size of non-tariff barriers, the relative location of reference markets and competitors, or the exposure to exchange rate risk.

Our empirical model with heterogeneity derives from gravity theory in Anderson and van Wincoop (2003), Anderson and van Wincoop (2004) and Baldwin (2006a), and links trade to trade costs, multilateral resistance terms, and economic activity. Our panel data set comprises monthly trade data with a two-dimensional cross section, country pairs and trade sectors. We implement heterogenous impacts of trade costs on trade by assuming that, conditional on a country-pair, model parameters depend linearly on a measure of the relative size of a trade sector. To address long-lasting changes in trade costs we specify a smooth transition path for each trade sector in each country pair. Smooth transition is a logistic distribution function with three parameters (LSTAR, Teräsvirta (1994)). Each parameter governs one dimension of transition, namely magnitude, speed, and timing. Moreover, the LSTAR model is sufficiently general to reflect long-run effects as transition is not enforced to complete within sample.

A special case of LSTAR transition is a dummy variable which turns unity with the introduction of the euro in January 1999. However, we allow the model to self-select magnitude, speed, and timing of transition rather than adopting a dummy specification since it seems difficult to justify a level shift in trade costs in January 1999 a-priori.[1] One alternative to smooth transition is to interact consecutive euro dummies with time dummies. We prefer smooth transition since interaction dummies make it hard to disentangle the three dimensions of transition into three distinct parameters. A further merit of the parsimonious parametric transition model is that interaction dummies easily become intractable if sector-specific timing patterns are of interest. With sector-specific transition paths in hand, we take a (weighted) mean-group perspective to quantify area-wide transition. We also average sectoral transition paths for country pairs outside the euro area. Then, "difference-in-difference" estimates of the euro's aggregate trade effect are determined by subtracting area-wide transition from the aggregate transition of country pairs outside the euro area.

We find that, due to a decrease in long-lasting trade costs, aggregate trade within the euro area increases between 2000 and 2002 by 15 to 25 percent compared with trade between European countries which are not members of the euro area. Parameter heterogeneity substantially improves the model's fit to the data despite the rather stylized form of heterogeneity we employ. Disaggregating the overall decrease in long-lasting trade costs uncovers a large amount of heterogeneity in country-pair and sector-specific adjustment. Moreover, whereas adjustment of aggregate trade costs requires two to three years to reach a new level, adjustment at the sector level is much faster. Aggregate adjustment is more spread out and gradual since different sectors adjust at distinct points in time. Rapid adjustment at the sector level squares well with recent microfoundation of the euro's trade effect in Baldwin and Taglioni (2004). These authors argue that the euro introduction induces considerable firm entry in export markets.

Our findings regarding the aggregate decrease in long-lasting trade costs differ in two main respects from the literature. First, we find that long-lasting trade costs adjust after the introduction of the euro in January 1999. Related studies also report adjustment before the introduction of the euro, and interpret this finding as anticipation effects. Second, we find a rather large mean effect

[1] Berger and Nitsch (2008) argue that several major events are candidates for shifts in euro-area trade costs even though January 1999 has become the convention. For our sample period from January 1995 to May 2006, alternative dates are the end of 1997 (the the third stage of the Economic and Monetary Union (EMU) is introduced), January 1999 (factual start of the third stage of EMU) and January 2002 (introduction of the euro as physical currency). Micco, Stein, and Ordonez (2003) and Flam and Nordström (2006b) report an increase in euro-area trade already in 1998, and interpret this increase as anticipation effect. DeNardis and Vicarelli (2007) argue that the euro may create medium to long-run trade effects because home bias in preferences extends to former foreign markets in the course of time.

of the euro on aggregate trade relative to what Baldwin, DiNino, Fontagne, Santis, and Taglioni (2008) call a consensus estimate of 5 to 15 percent.[2] Interestingly, fitting a single euro dummy which shifts in January 1999 to our aggregate smooth-transition path delivers a mean effect much closer to consensus. Turning to the degree, at which heterogeneity of transition paths affects the overall magnitude of transition, we find that heterogeneity matters for short-run trade effects of the euro as a consequence of country-pair and sector-specific timing.

Baldwin (2006a), Baldwin (2006b) and Baldwin, DiNino, Fontagne, Santis, and Taglioni (2008) review the literature on the trade effect of the euro.[3] Several papers in this literature relate to this article. Micco, Stein, and Ordonez (2003), Flam and Nordström (2006a), Flam and Nordström (2006b), and DeNardis and Vicarelli (2007) make inference on the timing of the euro's trade effect by means of consecutive time dummies interacted with a euro dummy. Baldwin, Skudelny, and Taglioni (2005) and Flam and Nordström (2006b) analyze sectoral trade data and estimate either sector-specific or country-pair specific coefficients. Nitsch and Pisu (2008) analyze firm and product-level trade data. With a particular application to currency union effects, Novy (2010) derives a gravity model for aggregate trade from a translog expenditure function in which trade costs have a heterogeneous impact on trade. In such a setting, a currency union stimulates bilateral trade if the exporter provides only a small share of the partner's imports. Otherwise, the currency union effect is weak. Chen and Novy (2010) derive a measure of bilateral trade integration, which accounts for cross-sector heterogeneity through substitution elasticities, and identify a large degree of trade-cost heterogeneity in sectoral data. Cheng and Wall (2005) estimate heterogeneity in the fixed effects of country pairs and show that, unless heterogeneity is accounted for correctly, gravity models overestimate the effects of integration on trade. Fratianni and Kang (2006) find that the distance-elasticity in their gravity model is not homogeneous across countries and that this result is highly statistically significant. Our approach to cross-section heterogeneity is to include bilateral country-pair fixed-effects, and to specify all trade-costs elasticities by means of functional regression.

The remainder of the paper is organized as follows. Section 2 briefly outlines gravity theory and explains how we account for multilateral resistance terms and unobserved trade costs. Section 3 describes the empirical model, functional regression, and estimation. Section 4 describes the data, and section 5 contains model selection and diagnostic checking. Section 6 discusses our results.

[2]The preferred estimate in Baldwin, Skudelny, and Taglioni (2005) is a 25% increase in intra-EU trade flows.
[3]Silva and Tenreyro (2010) review the recent literature on currency unions more generally.

## 2 Theory and Measurement

Gravity theory relates exports to the product of foreign expenditure and home production and to trade costs relative to multilateral resistance terms,

$$X_k^{ij} = E_k^j Y_k^i \left( \frac{\tau_k^{ij}}{\Pi_k^i P_k^j} \right)^{1-\sigma_k} . \tag{1}$$

Nominal exports of reporter country $i$ to partner country $j$ in sector $k$ are denoted $X_k^{ij}$, nominal expenditure in this sector is $E_k^j$, and nominal production is $Y_k^i$. The sectoral elasticity of substitution for exports from different origins is $\sigma_k > 1$. The trade cost function $\tau_k^{ij}$ summarizes trade costs between $i$ and $j$ and is specified below.

Variables $P_k^j$ and $\Pi_k^i$ represent inward and outward multilateral resistance, respectively.[4] Both terms are weighted averages of bilateral trade costs relative to the welfare-based price levels of the respective trading partner. Weights reflect the size of a sector. In particular, if importing country $j$ faces high trade costs with respect to exporters other than $i$ this increases inward multilateral resistance $P_k^j$ such that exports from $i$ to $j$ increase. Outward multilateral resistance $\Pi_k^i$ reflects the notion that, if from $i$'s perspective trade costs are higher for markets other than $j$, more will be exported from $i$ to $j$.

Multilateral resistance terms $P_k^j$ and $\Pi_k^i$ comprise a first set of variables which are difficult to measure. Multilateral resistance terms require a stand on which foreign sectors compete with national sectors. Since we necessarily work with a limited trade matrix comprising Germany, France, Italy, the United Kingdom, Sweden, and Denmark, we are likely to miss important substitutes. Furthermore, Baier and Bergstrand (2001), Feenstra (2003), and Anderson and van Wincoop (2004) point out that export and import price-indices do not align with multilateral resistance terms because such indices do not reflect home bias in preferences. A second set of variables which are difficult to measure consists of trade costs $\tau_k^{ij}$. Detailed data on trade costs are rare in general and even more difficult to obtain at monthly frequency and at the sectoral level of disaggregation. For a recent survey of trade costs and their availability see Anderson and van Wincoop (2004).

In our empirical model, we capture both multilateral resistance terms and omitted trade costs by means of a latent but time-varying variable on the right-hand side of our specification. The latent variable is specific to each country pair and to each trade sector such that it can indeed absorb variation in both omitted trade costs and resistance terms. Kalman filtering provides a conceptually

[4] Equation (1) is identical to equation (5) in Anderson and van Wincoop (2004) except that it absorbs world output into one resistance term.

straightforward account for latent and time-varying variables. The Kalman-filter specification is very parsimonious and thereby acknowledges the short (data) history of the euro. Admittedly, we exchange parsimony against some computational complexity since state-space modeling requires numerical optimization.

Applying the Kalman filter to the gravity model is not original to our paper. Sanz (2000) and Sanz and Gil (2001) apply the Kalman filter to measure the evolution of trade integration over time by means of time-varying coefficients. Recalde and Florensa (2006) employ the methodology of Sanz (2000) to analyze the trade-integration effects of Mercosur. Our application is slightly different because we use the Kalman filter to control for variation in time-varying but unobserved trade costs and in difficult-to-measure resistance terms rather than implementing time-varying coefficients.

An alternative approach to control for time-varying resistance terms, which is frequently adopted in the literature, is to add two sets of time dummies distinguishing the reporting and the partner country. Such a specification aligns well with equation (1) which implies two resistance terms per sector, one specific to the reporting country and the second one specific to the partner country. With $K$ trade sectors per country, $N$ countries, $T$ time periods, and thus $KN(N-1)T$ observations one has to add $2KNT$ dummies to control for sectoral resistance terms. Thus, as long as $N$ is large, the time-dummy solution is feasible but wipes out many degrees of freedom.

However, the time-dummy solution cannot cope with omitted trade costs which are specific to sectors and country pairs since adding one set of time dummies for each sector per country pair exhausts all degrees of freedom. Nevertheless, omitted trade costs are likely to bias coefficient estimates. Baldwin and Taglioni (2006) show that incomplete account of time variation in trade costs or multilateral resistance terms is likely to cause omitted-variable bias in parameter estimates.

# 3 Empirical Model

## 3.1 Basic Setup

We interpret equation (1) as state-space system. This interpretation delivers a conceptually straightforward account of unobserved trade costs and multilateral resistance terms. The log-linear equation (1) jointly with a specification of measurable components of trade costs represents the observation equation of the state-space system. Multilateral resistance terms and omitted trade costs are absorbed into the state equation. Here, we describe the most general panel model considered. We conduct specification tests below for nested models.

Let $i$ denote reporters, $j$ partners, $k$ sectors and $t$ time. Subsume reporter and partner indices under the trade-relationship index $s = ij, i \neq j$ and let $S$ (or $K$ or $T$) denote the maximum number of trade relationships (or sectors or time instances). For each trade relationship $s$ we estimate the following model,

$$y_{kt}^{(s)} = q_{it}\beta_{ik}^{(s)} + q_{jt}\beta_{jk}^{(s)} + (1-\sigma^{(s)})[\,\ln(\tau_{kt}^{(s)}) + \lambda_{kt}^{(s)}\,] + u_{kt}^{(s)}, \quad (2)$$

$$\ln(\tau_{kt}^{(s)}) = \theta_{0k}^{(s)}\left[1+\exp\{-\theta_{1k}^{(s)}(\tilde{t}-\zeta_k^{(s)})\}\right]^{-1} + (Z_t^{(s)})'\boldsymbol{\gamma}_k^{(s)} + c^{(s)}, \quad (3)$$

$$\lambda_{kt}^{(s)} = \lambda_{kt-1}^{(s)} + v_{kt}^{(s)}, \quad (4)$$

$$u_{kt}^{(s)} \sim N(0, g_k^{(s)}) \quad , \quad v_{kt}^{(s)} \sim N(0, h_k^{(s)}) \quad , \quad E[u_{kt}^{(s)} v_{kr}^{(s)}] = 0 \quad \forall t, r. \quad (5)$$

The observation equation (2) specifies the log of sector $k$ exports $y_{kt}^{(s)}$ for trade relationship $s$ conditional on scale variables $q_{it}$ and $q_{jt}$, the log of measurable trade costs $\tau_{kt}^{(s)}$, and the log of unobserved trade costs and multilateral resistance terms subsumed into $\lambda_{kt}^{(s)}$.

Equation (3) formalizes the log of measurable trade costs as a smooth-transition path (in square brackets) plus measurable control variables $Z_t^{(s)}$ and a constant term $c^{(s)}$.[5] Following Luukkonen, Saikkonen, and Teräsvirta (1988), smooth transition is specified as a logistic distribution function where $\theta_{0k}^{(s)}$ measures the magnitude of transition while $\theta_{1k}^{(s)} > 0$ governs the speed of transition. In order to immunize $\theta_{1k}^{(s)}$ against the scale of the time index $t$ the latter is standardized as $\tilde{t} = t/(T \times \sqrt{0.08333})$ (Bauwens, Lubrano, and Richard (2000)). Owing to the symmetry of the logistic distribution function we refer to $\zeta_k^{(s)}$ as the timing of transition. Jointly, the three coefficients $\theta_{0k}^{(s)}, \theta_{1k}^{(s)}$ and $\zeta_k^{(s)}$ fully describe the transition path. For instance, a large positive coefficient $\theta_{0k}^{(s)}$ implies a large magnitude of transition; a large positive coefficient $\theta_{1k}^{(s)}$ implies rapid transition; and a large positive coefficient $\zeta_k^{(s)}$ refers to a transition that takes place late in our sample. The smooth-transition path comprises an instantaneous and exhaustive level shift as special case.

In terms of theory, the state equation (4) reflects sector-specific omitted trade costs and multilateral resistance terms. We specify the collection of these variables as random walk which supposes a large degree of persistence in these variables and adds a dynamic aspect to our empirical specification of gravity theory. International relative prices and observable trade costs indeed exhibit

[5]The constant absorbs the usual time-invariant gravity variables such as common language or bilateral distance.

a large degree of history dependence. It thus seems a fair guess to expect similar behavior for difficult-to-measure multilateral resistance and unobserved trade costs. For instance, Berger and Nitsch (2008) and Mongelli, Dorrucci, and Agur (2005) argue that European integration is continuously deepening. Berger and Nitsch (2008) approximate such integration by a deterministic time trend. However, the diverse measures of European integration in Mongelli, Dorrucci, and Agur (2005) might be better described by stochastic trending rather than in terms of deterministic time patterns.[6] Therefore, specifying $\lambda_{kt}^{(s)}$ as random walk is a parsimonious but seemingly appropriate time-series description also for measures of European integration.

As a side benefit, the state-space model allows the quantification of the elasticities of substitution $\sigma^{(s)}$. In related studies, this parameter is due to the use of time dummies often not identified. Hence, as an additional evaluation of the model's plausibility, it will be of interest if estimated substitution elasticities conform with consensual guesses or estimates drawn from the more specific literature, e.g. Broda and Weinstein (2006).

Control variables $Z_t^{(s)}$ comprise exchange-rate volatility $vol_t^{(s)}$ (described below), and an index of energy prices $en_t^{(s)}$ as an approximation of transportation cost components. Furthermore, $Z_t^{(s)}$ comprises real effective exchange rates of the reporting country $reer_t^{(s)}$, real bilateral exchange rates between both trading partners $rex_t^{(s)}$, and real billateral exchange rates of the reporting country relative to the U.S. $rexus_t^{(s)}$. Adding bilateral exchange rates gives a prominent role to these two relative prices beyond their appearance in the real effective exchange rate. Appendix E describes the construction of real exchange rates. Flam and Nordström (2006b) and Baldwin (2006a) emphasize that exchange rates help to discriminate potential expenditure-switching effects from effects of introducing the common currency. When the euro depreciated after its introduction, goods sold in euro became relatively cheap such that parts of euro-area demand for foreign goods was possibly redirected back to the euro area.

The dependent variable $y_{kt}^{(s)}$ in equation (2) is likely to be nonstationary.[7] In this case, the empirical model may suffer from spurious findings in the sense that coefficient estimates of nonstationary right-hand variables fail consistency. Balancing the regression model (2) – (5) requires at least one nonstationary variable on the right-hand side. We regard scale variables $q_{it}$ and $q_{jt}$, exchange rates, and unobserved state variables in (4) as candidates to cointegrate with $y_{kt}^{(s)}$. Chang,

[6] See figures 1 to 4 in Mongelli, Dorrucci, and Agur (2005).

[7] Unit-root tests powerfully underscore the likelihood of stochastic trends in $y_{kt}^{(s)}$. In light of the plentitude of time series entering the empirical models we refrain from a provision of detailed results on unit-root testing. Doing so reveals that, almost uniformly, first differences of employed time series are stationary so that the highest order of stochastic trending is unity.

Miller, and Park (2009) show that the common (Quasi) Maximum Likelihood (QML) interpretation of modeling stationary processes by means of the Kalman filter also applies for multivariate nonstationary processes which share a common trend. As a consequence, the validity of standard specification tests, e.g. likelihood ratio (LR) tests, does not rely on the stationarity of $y_{kt}^{(s)}$ or conditioning variables.

### 3.2 Functional Coefficients and Estimation

We collect all coefficients in the two vectors

$$\boldsymbol{\Psi}_k^{(s)} = \left(\beta_{ik}^{(s)}, \beta_{jk}^{(s)}, \theta_{0k}^{(s)}, \theta_{1k}^{(s)}, \zeta_k^{(s)}, \boldsymbol{\gamma}_k^{(s)\prime}, h_k^{(s)}, g_k^{(s)}\right)' \quad \text{and} \quad \boldsymbol{\phi}^{(s)} = (\sigma^{(s)}, c^{(s)})',$$

where $\boldsymbol{\Psi}_k^{(s)}$ and $\boldsymbol{\phi}^{(s)}$ comprise sector-specific and sector-invariant coefficients, respectively. To estimate $\boldsymbol{\Psi}_k^{(s)}$ we presume a parsimonious functional representation in which sector-specific coefficients equal a common intercept term and a slope coefficient multiplied by a sector-specific scalar $a_k^{(s)}$,

$$\boldsymbol{\Psi}_k^{(s)} = (\mathbf{1} + \boldsymbol{\psi}_1^{(s)} a_k^{(s)}) \odot \boldsymbol{\psi}_0^{(s)} \ . \tag{6}$$

Here $\mathbf{1}$ is a unit vector of appropriate dimension, and $\boldsymbol{\psi}_1^{(s)}$ and $\boldsymbol{\psi}_0^{(s)}$ are vectors of unconditional coefficients that are specific to the country pair. The operator '$\odot$' signifies 'element-by-element' multiplication and the scalar $a_k^{(s)}$ with $\sum_k a_k^{(s)} = 1$ reflects the importance of sector $k$ in reporting country $i$. To be precise, denote the relative average quantity traded in sector $k$ as $w_k^{(s)}$. The importance of sector $k$ then is $\tilde{a}_k^{(s)} = \tilde{w}_k^{(s)}/(\sum_k \tilde{w}_k^{(s)})$, with $\tilde{w}_k^{(s)}$ denoting the rank associated with $w_k^{(s)}$ in sector $s$. Then, a mean-zero weighting sequence is $a_k^{(s)} = \tilde{a}_k^{(s)} - (1/K)\sum_k \tilde{a}_k^{(s)}$. Appendix A describes the computation of weights.

Equation (2) restricts the elasticity of substitution $\sigma^{(s)}$ to be common for all sectors conditional on country pair $s$. Assuming instead a linear functional relationship in the elasticity of substitution implies a quadratic functional relationship in the elasticity of export with respect to, say, controls $Z_t^{(s)}$. The quadratic relationship follows because elasticities comprise the product of $\sigma^{(s)}$ and coefficients which already depend linearly on the functional variable $a_k^{(s)}$. We avoid such quadratic relationships by imposing $\sigma_k^{(s)} = \sigma^{(s)}$.

Ideally, sector-specific coefficients $\boldsymbol{\Psi}_k^{(s)}$ should be flexible enough to reflect the many dimensions which make sectors transit differently and respond differently to changes in control variables. To name only a few, sectors are likely to differ with respect to the intensity of competition, with respect to pricing strategies and strategic interaction, or regarding the degree of product substitutability. Our functional specification pretends that all relevant dimensions are reasonably well represented by a sector's market size which is obviously not the case. However, besides being an operative measure, we believe that market size is a useful functional variable in that it correlates with at least the more relevant dimensions.[8]

QML estimation of the empirical model requires iterative optimization due to nonlinearities in model parameters and the presence of the unobserved processes $\lambda_{kt}^{(s)}$. A few parameters of the state-space model are estimated conditional on a restricted support. First, variance parameters are determined as exponentials of underlying parameters,

$$g_k^{(s)} = \exp\left(\underline{g_k^{(s)}}\right) \quad \text{and} \quad h^{(s)} = \exp\left(\underline{h_k^{(s)}}\right) \; .$$

Underlining signifies that log-likelihood optimization is done, for instance, with respect to $\underline{g_k^{(s)}}$ rather than $g_k^{(s)}$.

The second set of restrictions applies to coefficients of the smooth-transition function. The term in squared brackets in equation (3) degenerates to a constant as $\theta_{k1}^{(s)}$ tends to zero. In this case, the state-space model might lack identification as it already comprises a constant term. Accordingly, we restrict the support of $\theta_{k1}^{(s)}$ to strictly positive values. Furthermore, fastest 90% of transition is restricted to one month by imposing $\theta_{k1}^{(s)}$ to be smaller than 232.89. Also, we impose bounds on the support of the timing parameter $\zeta_k^{(s)}$ to prevent the transition function from isolating the first and last year of the sample. Within these bounds, the timing parameter is free to adjust. We implement parameter restrictions with the cumulative Gaussian $\Phi$, $0 < \Phi < 1$, as

$$\theta_{1k}^{(s)} = 232.89\ \Phi(\underline{\theta_{1k}^{(s)}}) \quad \text{and} \quad \zeta_k^{(s)} = 0.30343 + 2.8826\ \Phi(\underline{\zeta_k^{(s)}}).$$

Appendix B provides further details to obtain such bounds. Finally, we ensure $\sigma^{(s)} > 1$ in line with economic theory. For optimizing over explicit or underlying parameters to obtain $(\boldsymbol{\Psi}_k^{(s)\prime},\ \boldsymbol{\phi}^{(s)\prime})'$ the *optmum* routine in GAUSS is used.

[8] Alternative functional variables would be the number of firms, profits, markups, measures of exchange rate pass through, or fixed costs of production. Besides data availability, relying on several functional variables would considerably boost the parameter space and render optimization overly challenging at this stage. Factor analysis is one means to reduce dimension and may offer an interesting extension of the setup considered here.

# 4 Data

We investigate monthly bilateral export data from January 1995 to May 2006 (137 months). Monthly data are considered to collect as much information as possible around the hypothesized break point. In EUROSTAT's COMEXT database, export data is available in value (current euro) and volume (tons) and is disaggregated according to the HS two-digit level. The HS classification provides a break down of aggregate trade into 99 trade sectors of which we consider $K = 96$.[9] We convert export data into year 2000 euros.

The trade matrix comprises Germany, France, Italy, United Kingdom, Sweden, and Denmark so that we obtain $S = 30$ country pairs. We restrict attention to European Union (EU) member states to maintain as much homogeneity as possible along the country dimension. In terms of euro-area countries, we focus on Germany, France, and Italy. These economies are of interest because they cover a major fraction of the euro area both in terms of population and of GDP. The United Kingdom, Sweden, and Denmark are interpreted as control group to infer the trade effect of the euro on euro-area countries by "difference-in-difference" estimation.[10] For meaningful "difference-in-difference" estimates, it is important to maintain a control group as comparable as possible to euro-area countries. The United Kingdom, Sweden, and Denmark constitute a meaningful control group since these countries experienced a history similar to euro-area countries except for the introduction of the common currency. For instance, all EU countries have been exposed to similar legislation and regulation in the wake of the European Single Market initiative after 1993. By choosing EU countries without the euro as control group, we make sure that we also control for the many unobserved facetts of EU membership.

Out of the 30 country pairs, six involve countries which both have adopted the euro (U2), six involve countries which both have not adopted the euro (O2), nine involve countries where the reporting country has adopted the euro but the partner country has national currency (OUT), and nine involve countries where the partner country has adopted the euro but the reporter has not (IN). We compute mean-group estimates along the lines of Pesaran and Smith (1995) based on these subsets. Table 1 lists all country pairs explicitly.

At the two-digit level, trade data for some sectors are plagued by irregularly missing observa-

[9]See http://fd.comext.eurostat.cec.eu.int/xtweb/ for COMEXT database. Sectors 77 and 98 do not contain any data for our sample. We drop sector 99 ('Other Products'). HS abbreviates Harmonized Commodity Description and Coding System. Baldwin and Taglioni (2006) address a wide range of possible misspecifications of the gravity equation related to data construction.

[10]See Baldwin, DiNino, Fontagne, Santis, and Taglioni (2008) for more on "difference-in-difference" estimation in the context of the euro's trade effect.

tions. We do not exclude such sectors from our analysis since Kalman-filter recursions are easily modified to cope with irregularly missing observations. Hence, the empirical analysis does not suffer from imputed measures replacing missing observations, and is not subject to sample selection bias as a consequence of excluding a potentially nonrandom fraction of sectors from the analysis. Appendix C provides details on the employed Kalman filter recursions.

Theory suggests to use sectoral data for production and expenditure as scale variables. Rather than sectoral data, we use aggregate indices of industrial production as proxy for scale variables but allow for sector-specific coefficients $\beta_{ik}^{(s)}$ and $\beta_{jk}^{(s)}$ to mitigate inferior data quality. For two-digit trade sectors, Baldwin, Skudelny, and Taglioni (2005) compare a specification with sector-specific data on gross-value-added as proxy for scale variables with a specification which instead uses aggregate GDP data. They find that the magnitude of the change in trade costs is sensitive to the proxy for sectoral activity, but mention difficulties to obtain disaggregated data for gross-value-added. Flam and Nordström (2006b) report similar data problems with one-digit data at the annual frequency, and estimate sector-specific regressions with aggregate GDP data. In our case, data availability is even more a constraint and motivates the choice of industrial production as proxy for sectoral activity.

Finally, similar to Baldwin, Skudelny, and Taglioni (2005) nominal exchange-rate volatility is estimated nonparametrically as

$$\left(vol_t^{(s)}\right)^2 = \frac{1}{D_t}\sum_{d=1}^{D_t}\left(\Delta \ln e_d^{(s)} - \frac{1}{D_t}\sum_{d=1}^{D_t}\Delta \ln e_d^{(s)}\right)^2 . \tag{7}$$

In (7), $e_d^{(s)}$ represents daily quotes of reporter $i$'s currency in terms of partner $j$'s currency and $D_t$ is the number of days per month.

# 5 Model Selection

In this section, we identify our preferred specification by testing particular restrictions on the empirical model outlined in section 3. Results from model selection and diagnostic checking are documented in table 1. For model selection, we mostly employ likelihood ratio (LR) tests. The fact that we consider a set of 30 country pairs adds complexity to the provision of empirical results. In light of the plentitude of estimated empirical models, space considerations only allow a condensed overview of model features. Discussing the particular issues of model diagnosis and selection, we start with a diagnosis of the stochastic features of residuals $u_{kt}^{(s)}$ in (2) to guard against spurious regression. Next, as a further building block of the state space approach, the explanatory content of latent measures of resistance and unobservable cost components is addressed. Thirdly, the case of overall parameter heterogeneity is underlined by contrasting the fully unrestricted functional model against a restricted specification characterized by sector-invariant model parameters. Then, an overall perspective is offered at heterogenous transition features and, finally, the role of measurable exogenous controls on trade is briefly interpreted.

*(i) Stochastic Trends and Serial Correlation:* To diagnose stochastic trends governing model disturbances, we test the null hypothesis of nonstationarity for estimated residuals of the observation equation (2).[11] Empirical frequencies of rejections of the unit-root null hypothesis (column labeled 'I(1)' in Table 1) indicate that the conditional model is almost throughout successful in filtering out common stochastic trends. Unreported results show that the evidence against spurious regression is similarly strong when modeling trade dynamics by means of homogeneous conditional models. Having confirmed the stationarity of residual processes in (2), it is noteworthy that first order serial correlation is found for about one third of sector-specific residual series (column labeled 'AR1' in Table 1).[12] As a consequence, single parameter diagnosis might suffer from inferential biases and, consequently, overall empirical conclusions might be better drawn from the panel mean-group level.

*(ii) Latent Resistance:* To describe the explanatory content of states $\lambda_{kt}^{(s)}$, we estimate sector-invariant models imposing $\lambda_{kt}^{(s)} = 0, \forall s, k, t$ which implies that multilateral resistance and unobserved trade costs are time invariant and absorbed in the models intercept parameter. We then compare the resulting standard-error estimate $\sqrt{\hat{g}^{(s)}}$ with the corresponding quantity obtained from the homogeneous state-space model (column 'SR' in table 1). Although the reported standard error ratio is purely descriptive, it strongly underpins the explanatory content of unobserved variables. Excluding sector-specific unobserved variables involves a magnification of implied error variations by factors of 8.4 (exports of the UK to Denmark) up to 56.25 (French exports to Germany). At the first sight, these factors appear rather large. Noting, however, that $\lambda_{kt}^{(s)}$ might cointegrate with the sector-specific trade variables, a model without unobserved variables is likely

[11] Residual-based testing for unit roots compares standard ADF statistics with a 5% critical value of -4.74 (Fuller (1976)) which is the relevant critical value for a static regressions involving 6 nonstationary variables. The lag order of the ADF regression is 3 throughout. The critical value is likely conservative for the considered testing problem because the number of potential nonstationary right-hand variables in the state-space model is 3 when excluding exogenous control variables but including unobserved variables. Further, since estimated error sequences are not obtained from static cointegrating regressions, ADF tests provide a rather descriptive view at overall model reliability. For each of the 30 trade relationships up to 96 sector-specific time-series are subjected to testing.

[12] Testing against joint autocorrelation at lag 1 to 12, the empirical evidence against serially uncorrelated model residuals is even stronger. When comparing the functional against the homogeneous state-space model (not reported) diagnostic model features also support the more general model class. Almost uniformly the frequency of significant autocorrelation test statistics is lower for the functional as it is for the homogeneous state-space model.

to yield nonstationary residuals. Rather than deterministic time patterns, it appears that stochastic resistance terms are essential to keep the regression model balanced and to guard against spurious significance.

*(iii) Sector Heterogeneity:* Most strikingly, the functional state-space model with sector-specific coefficients is uniformly and significantly supported when compared with the homogeneous state-space model. Introducing 7 additional parameters, the smallest likelihood ratio statistic testing the functional against the homogeneous state-space model ($H_0 : \boldsymbol{\psi}_1^{(s)} = 0$ versus $H_1 : \boldsymbol{\psi}_1^{(s)} \neq 0$) is 635.7 (column $\mathrm{LR}_f$ in table 1). This statistic could be compared with critical values from a $\chi^2(7)$ distribution. However, all statistics are in favor of the functional state-space model at any conventional significance level despite the ad-hoc, rank-based formalization of parameter variation employed. By implication, the relative size of sectors seems to capture well the structural characteristics which matter for the impact of trade costs on trade. [13] We now turn to heterogeneity in the impact of exogenous controls and state variables.

*(iv) Exogenous Control Variables:* Augmenting the functional model jointly with all additional control variables $vol_t^{(s)}, reer_t^{(s)}, rex_t^{(s)}, rexus_t^{(s)}$ and $en_t^{(s)}$ delivers likelihood ratio statistics that are mostly significant (column '$\mathrm{LR}_X$' in table 1). With 5% significance, 18 (out of 30) trade relationships are characterized by a significantly improved model fit when including additional control variables. Marginal contributions of individual control variables are discussed in the next section.

*(v) Smooth Transition:* To assess the marginal contribution of the flexible smooth-transition path in comparison with a conventional level shift in trade costs, the state-space model with homogeneous coefficients ($\boldsymbol{\psi}_1^{(s)} = 0$) is alternatively estimated under restrictions $\theta_{1k}^{(s)} = 232.89$ and $\zeta_k^{(s)} = 1.2137$. These restrictions closely approximate a level shift in January 1999. For numerous trade relationships the smooth-transition specification is supported by significant LR statistics (column '$\mathrm{LR}_d$' in table 1). Out of 30 LR statistics 12 (5) are significant at the 10% (5%) level. To fully assess these diagnostics, it is worthwhile to note that LR statistics are interpreted to follow an asymptotic $\chi^2$ distribution with two degrees of freedom while their true distribution is likely to be unknown since the homogeneous state-space model itself is overly restrictive. Diagnosing the heterogeneity of transition parameters in the fully unrestricted model underlines that in particular the timing of transition is markedly sector-specific.

Summarizing the diagnostic and inferential evidence, the applied functional state-space model

[13] Furthermore, we explored heterogeneity of country-specific model-implied parameters by means of Analyses of Variance (ANOVA). It turns out that parameter variations within subsets of country pairs are also highly significant throughout. As a consequence, potential triggers of parameter heterogeneity constitute most likely an index from various sectoral and economy specific characteristics. Detailed ANOVA results are available on request.

results in balanced regressions and points to pronounced explanatory content of latent resistance and trade cost components. At the aggregate level both, measurable control variables and flexible transition paths contribute significantly to the empirical description of European trade patterns in a time period surrounding the monetary unification. Most strikingly, sector heterogeneity is a core feature of conditional trade patterns and, thus, of the estimated impact of the common currency. Challenging the econometric postulates of model parsimony and feasibility, potential triggers of sectoral heterogeneity are magnifold and also turn out to be country-specific. With this in mind, the adopted rank-based functional approach to the formalization of parameter variation compromises between the needs of flexible fitting of observed trade patterns and its reflection in quantitative specifications. We regard the functional smooth-transition state-space model covering the full set of exogenous control variables as the preferred model specification for which a detailed analysis of more structural implications is provided next.

# 6 Results

Table 2 reports estimated coefficients for the preferred model. The column labeled ALL provides mean-group coefficients as weighted averages over all sectors and over all country pairs. Weights correspond to relative sector size. Subsequent columns provide mean-group coefficients for the various subsets of country pairs U2, O2, IN and OUT. Subsets are described in section 4. Appendix A provides details on the computation of mean-group estimates. We start with inspecting coefficient estimates others than those that determine transition. Then, we turn to the characteristics of transition paths.[14]

## 6.1 Coefficient Estimates of Measurable Trade Costs and Scale Variables

Elasticities of substitution $\sigma$ in table 2 are roughly 5 and are tightly estimated. The estimates fall into the lower range of 5 to 10 as surveyed by Anderson and van Wincoop (2004). Broda and Weinstein (2006) report elasticities of substitution around 4 using SITC three-digit U.S. data for the period 1990–2001. Our estimates around 5 refer to two-digit European data for a slightly different classification (HS instead of SITC) but overall appear to comply with estimates in Broda and Weinstein (2006). This similarity is reassuring since the state-space model does not make use of international price data.

[14] We also estimate the model using import data. Overall, results are very similar even though estimates obtained from import data are somewhat less precise.

In line with theory, industrial production in the reporting ($\beta_i$) and partner ($\beta_j$) country significantly increases exports which holds true for all country pairs on average and for the majority of subsets. Though theory predicts a unit elasticity, three out of the eight estimates significantly differ from unity.[15] Estimates different from unity may signal ongoing change in the ratio of sectoral exports over industrial production. This explanation fits well with the high estimation accuracy for some coefficients. Also, Baldwin (2006a) argues that inferior data quality may be one factor pushing elasticities below unity. Indeed, our proxy of sectoral activity is identical for all sectors. Even though industrial production certainly is a reasonably accurate measure of economic activity in some sectors (say, 'Manufacturing'), it is likely to be less so for others (say, 'Food'). We do not find estimates significantly larger than unity.

Exchange-rate volatility is usually considered an impediment to trade and in particular so for small firms without the financial status to hedge exchange-rate risk.[16] In our sample, exchange-rate volatility *vol* has a tendency to promote trade with a small elasticity of 0.014. However, the positive relationship does not seem particularly robust. Theories which draw on the option value of trade predict such a positive link between trade and exchange rate uncertainty. Here, it appears more likely that the tendency of estimates to become positive relates to the trend decrease in exchange-rate volatility during the convergence towards the third stage of the European Monetary Union.

A high effective exchange rate, *reer*, decreases exports with elasticity -0.2 when taken over all country pairs. If domestic goods become more expensive relative to a weighted basket of foreign goods this reduces exports. However, the evidence over subsets is mixed so that the aggregate effect is not very precisely estimated. Real bilateral exchange rates, *rex*, do not add information suggesting that real effective exchange rates, *reer*, already reflect bilateral variation sufficiently well. In contrast, real bilateral exchange rates with the U.S., *rexus*, matter positively. The finding supports the expenditure-switching hypothesis: After January 1999 the euro fell sharply so that goods sold in euro became relatively cheap. As a consequence, European demand for foreign goods was redirected to European products fostering trade among European countries. Finally, the effect of energy prices is statistically significant when determined over all country pairs. High energy

[15] For sectoral data, Baldwin, Skudelny, and Taglioni (2005) report estimates for various specifications of scale variables which are significantly larger or smaller than unity for a non-negligible number of cases. Also, some of their estimates are significantly negative (see their appendix C). Similarly, Flam and Nordström (2006b) find several coefficients for scale variables which are significantly different from unity when employing sectoral data.

[16] Baldwin and Taglioni (2004) argue that due to firm entry and exit into the sector of traded goods the true effect of exchange rate uncertainty on trade is non-linear. Indeed, Herwartz and Weber (2005) find evidence for non-linearities in the effect of exchange rate uncertainty on trade growth.

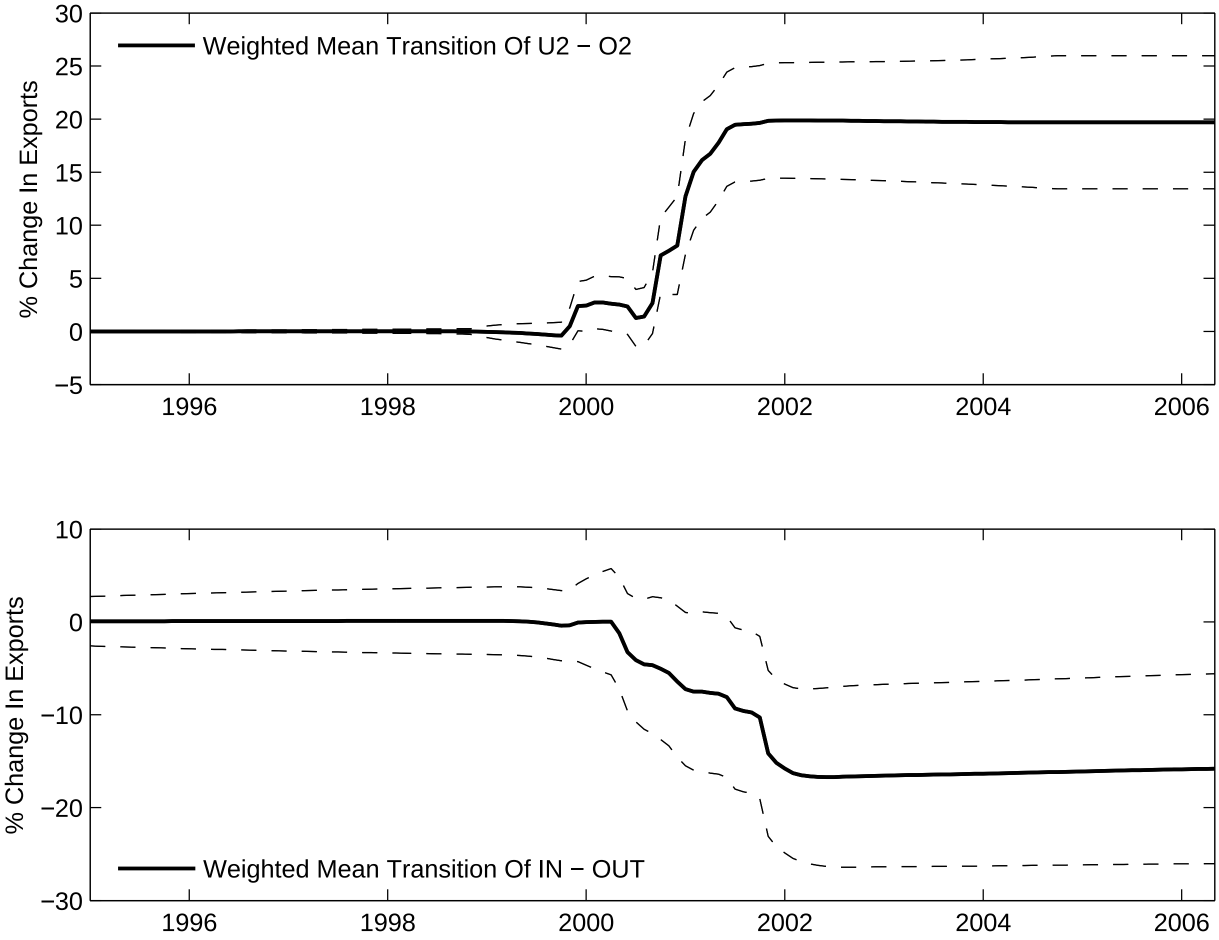


Figure 1: First panel shows weighted averages of sector-specific transition paths over country pairs in U2 minus the weighted average of sector-specific transition paths over country pairs in O2. Second panel shows the same quantity for country pairs in IN minus country pairs in OUT. All estimates are based on the functional smooth-transition state-space model. Confidence bands refer to the 10% significance level (see appendix A for computation).

prices reduce exports. To sum up, we find coefficient estimates which are mostly in line with results found in the previous literature and which comply reasonably well with theory.

### 6.2 Transition Dynamics

The smooth-transition function in specification (2) to (5) allows us disentangle three dimensions of transition, namely timing, speed, and magnitude. Each dimension is represented by one parameter, $\zeta_k^{(s)}$, $\theta_{k1}^{(s)}$, and $\theta_{k0}^{(s)}$, respectively.[17] Figure 1 shows the percentage change in exports derived from estimated smooth-transition. The top panel shows the weighted average transition path for country pairs in U2 minus the weighted average transition for country pairs in O2. The bottom panel shows

[17]In the literature, a main focus has been on a single dimension of euro transition, its magnitude. Those studies (cited in the introduction) which infer on the timing of the euro effect do so by interacting year dummies with consecutive euro dummies. With such a specification, it is less clear how to separate timing, speed, and magnitude of transition.

weighted average transition for country pairs in IN minus weighted average transition for country pairs in OUT. Weighted average transition paths are averages over transition paths specific to each sector in each country pair. Corresponding weights are relative sector size $w_k^{(s)}$ normalized to sum to unity for each subset. By considering the difference between transition in U2 and O2 (IN and OUT) we pursue a "difference-in-difference" interpretation of our estimates. That is, we treat country pairs in O2 as control group for country pairs in U2, and country pairs in OUT as control group for those in IN.

Exports within the euro area (U2) increase by 15 to 25 percent between the years 2000 and 2002 compared with exports between European countries that are not members of the euro area (O2). According to our estimates, it takes roughly two to three years for euro-area exports to reach a new level. However, euro-area trade appears to start its transition only one year after the fixing of exchange rates in January 1999. We return to this point below.[18] The bottom panel of figure 1 indicates that net exports of countries within the euro area to countries outside the euro area fall by about 15 percent, though this estimate is surrounded by considerable uncertainty. Moreover, figure 1 reveals a tight coincidence in terms of timing between U2/O2 transition and IN/OUT transition. Given that we do not restrict timing coefficients, this coincidence of transition dynamics between euro-area countries and the United Kingdom, Sweden, and Denmark appears to be an important feature of the data.

Overall, net exports of euro-area countries to European countries which have not adopted the euro fall. This finding jointly with the tight coincidence of the timing between U2/O2 and IN/OUT transition is consistent with the following economic interpretation.[19] The introduction of the euro creates stiffer competition among euro-area exporters thereby depressing price markups. A part of euro-area trade with third countries is redirected back into the euro area increasing exports within euro area. At the same time, third countries import more from the euro area because euro-area goods become cheaper relative to goods in the United Kingdom, Sweden, and Denmark. We now discuss transition dynamics in greater detail.

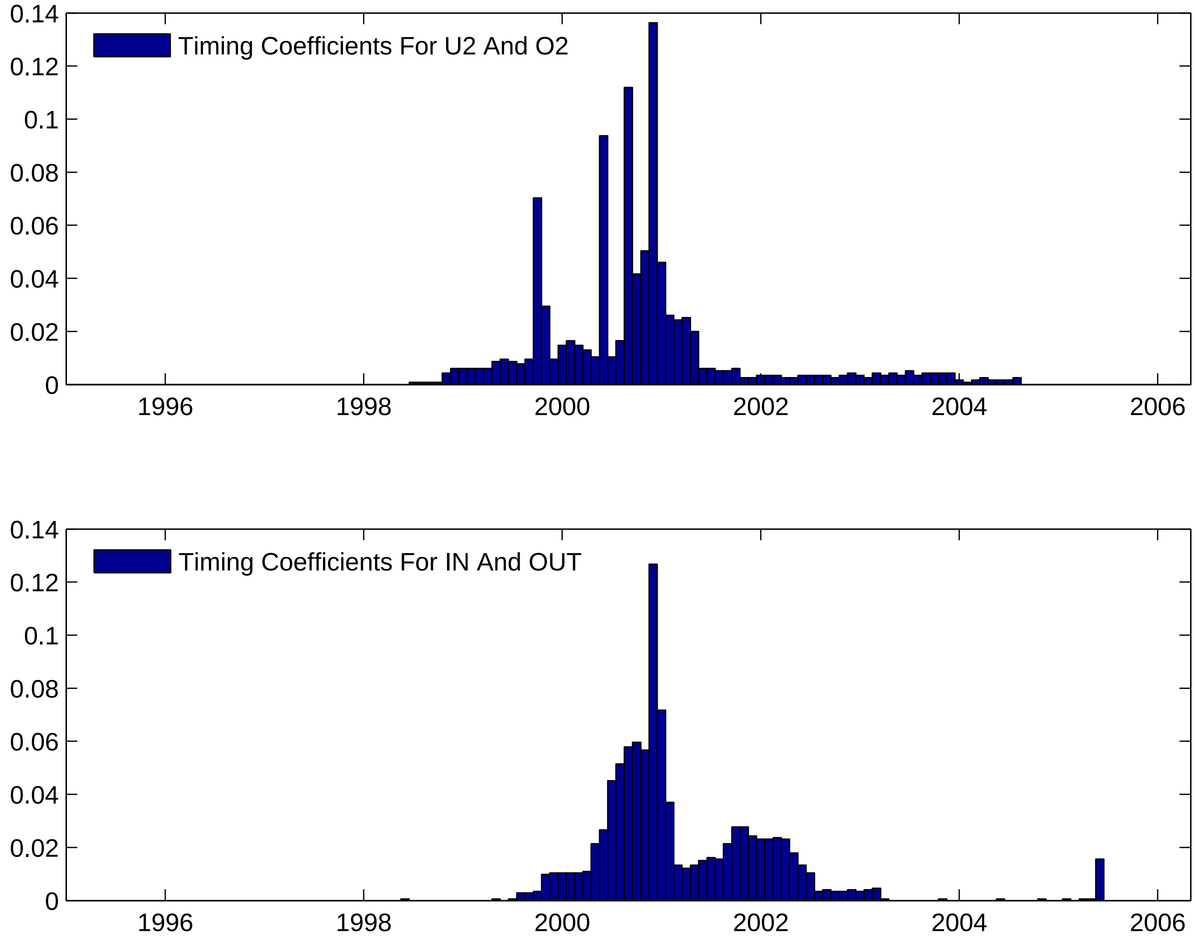


Figure 2: First panel shows estimated timing coefficients $\zeta_k^{(s)}$ after conversion into month for country pairs in U2 and O2. Second panel shows estimated timing coefficients $\zeta_k^{(s)}$ after conversion into month for country pairs in IN and OUT. All estimates are based on the functional smooth-transition state-space model. See appendix B for computational details.

### Speed and Timing

Aggregate exports require roughly two to three years to adjust to their new level which is true for exports within the euro area relative to exports among outsiders and for net exports between euro-area countries and outsiders. However, adjustment at the sector level is much faster on average which becomes evident from the mean-group estimates of transition speed $\theta_{1k}^{(s)}$ in table 2. To simplify interpretation, we convert speed estimates into the number of months a sector requires to complete the 99 percent of core transition.[20] The weighted average number of months for transition across

[18]Clearly, we don't find the anticipatory activity in euro-area trade before January 1999 reported in Micco, Stein, and Ordonez (2003) and Flam and Nordström (2006b). One interpretation of this difference might be that anticipation effects in fact are spurious findings due to unaccounted time variation in country-pair specific or sector-specific trade costs.

[19]This interpretation is not original to our paper. For a review of the literature, see Baldwin, DiNino, Fontagne, Santis, and Taglioni (2008).

[20]Convert $\theta_1$ into month by $t_{1-\alpha} - t_\alpha = 2T\sqrt{0.08\overline{3}}/\theta_1 \ln((1-\alpha)/\alpha)$ with $\alpha = 0.005$ (see appendix B for details).

all country pairs is close to 5 with standard deviation 3.4 which is considerably less than the two to three years observed for aggregate transition. The short duration of transition for an average sector prevails throughout subsets. For subsets U2, O2, IN and OUT, the weighted average number of month for transition is 6.184 (2.243), 2.856 (4.385), 2.953 (3.822), 5.447 (10.546) with standard errors in parenthesis.

The main reason for adjustment of aggregate exports to be more spread out and gradual is that different sectors adjust at distinct times. Table 2 reports the mean-group estimates of transition timing $\zeta_k^{(s)}$ which indicates 50% of completed transition. For interpretation, figure 2 converts estimated timing coefficients into month, and provides their relative frequencies for each month in our sample.[21] Two observations emerge from the figure. First, estimated timing coefficients are centered somewhere around 2001. The finding is quite striking since the model self-selects timing coefficients freely from the data. Second, estimated timing coefficients are dispersed. For U2 and O2 subsets, timing coefficients cluster between 1999 and 2002 with some estimates fanning out up to 2004. For IN and OUT subsets, timing coefficients cluster between 2000 and 2003 with some outliers towards the end of the sample. The dispersion of timing coefficients implies that, even though individual sectors adjust rapidly, aggregate adjustment is much more spread out and gradual.

Once uncovered, such rapid adjustment at the sector level fits well with recent micro-foundations of the euro's trade effect first put forth by Baldwin and Taglioni (2004). These authors argue that trade adjustment to the euro is fast because reduction of exchange-rate volatility induces a large number of small firms to enter export markets.

**Magnitude**

The magnitude of transition in figure 1 is the dimension that compares most easily to existing studies. Mean effects at the end of our sample in May 2006 are close to 20 percent for the difference between U2 and O2 countries.[22] Baldwin, DiNino, Fontagne, Santis, and Taglioni (2008) summarize the literature on the euro's trade effect as suggesting a positive trade effect of monetary unification of about 5 to 15 percent. Accordingly, our long-run mean estimate is higher than what commonly has been reported even though confidence bands comprise long-run effects of 15 percent in size. In the next section, we argue that one reason for our estimates to be larger than those commonly

[21] The conversion is $t_k^{(s)} = 2T\sqrt{0.08\bar{3}}\zeta_k^{(s)}$.

[22] The major bulk of this change comes from a reduction of exports among O2 countries (not shown) rather than an increase of trade among U2 countries. One interpretation is that exports in both U2 and O2 countries were hit by adverse shocks around 2000 but that the introduction of the common currency prevented trade among U2 countries to fall as sharp as trade among O2 countries did.

obtained relates to speed and timing of sectoral transition.

### 6.3 Mapping Smooth Transition into Euro Dummies

In this section, we relate our estimate of the euro's trade effect obtained from smooth transition to estimates obtained from a euro dummy which is frequent in the related literature. To do so, we pretend that our transition paths indeed are unbiased estimates of their true counterparts, and fit euro dummies to these transition paths under distinct assumptions regarding parameter heterogeneity and the timing of the euro dummies. Of course, such an exercise is open to the objection that smooth transition paths are subject to measurement errors. For instance, we employ a very stylized form of parameter heterogeneity, and some researchers may not agree with the exogenous control variables we include, or with the representation of omitted trade costs and resistance terms as random-walk state variables. Nevertheless, conditional averaging of data-selected transition paths is useful to uncover robustness of estimates of the euro's trade effect obtained from specifications with dummies and homogenous parameters.

To be precise, let $ST_t^{u2}$ denote weighted average smooth transition in subset U2 in percent of exports. Let $D_{t^\star}^{u2}$ denote a dummy which shifts from zero to unity at time $t^\star \in [1,T]$ and which is specific to country pairs in U2. With a similar notation applying to O2 the pooled regression with homogenous coefficients is

$$\begin{pmatrix} ST_t^{u2} \\ ST_t^{o2} \end{pmatrix} = \begin{pmatrix} D_{t^\star}^{u2} & 0 \\ 0 & D_{t^\star}^{o2} \end{pmatrix} \begin{pmatrix} \delta^{u2} \\ \delta^{o2} \end{pmatrix} + \epsilon_t \ .$$

We compare the difference of dummy coefficients $\delta^{u2} - \delta^{o2}$ to the difference of transition paths $ST_t^{u2} - ST_t^{o2}$ for each possible timing of the two dummy variables, $t^\star \in [1,T]$. In addition to pooled estimates, we also compute sector- and country-pair specific estimates. Let $ST_{kt}^{(s)}$ denote smooth transition in sector $k$ of country pair $s$ at time $t$ in percent of exports. Let $D_{t^\star}$ denote a dummy which shifts from zero to unity at time $t^\star \in [1,T]$. The regression is

$$ST_{kt}^{(s)} = \alpha_k^{(s)} D_{t^\star} + \epsilon_{kt}^{(s)} \ ,$$

for all $s$ in U2 and O2 and $k = 1, \ldots K$. We compute weighted averages over coefficients $\alpha_k^{(s)}$ for subsets U2 and O2 analogously to the weighted average transition paths, and denote them as $\alpha^{u2}$ and $\alpha^{o2}$, respectively. Moreover, corresponding regressions are obtained for country pairs in IN and

OUT. Overall, there are 2880 transition paths of which 576 belong to the six country pairs in U2 and O2, and of which 864 belong to the nine country pairs in IN and OUT.

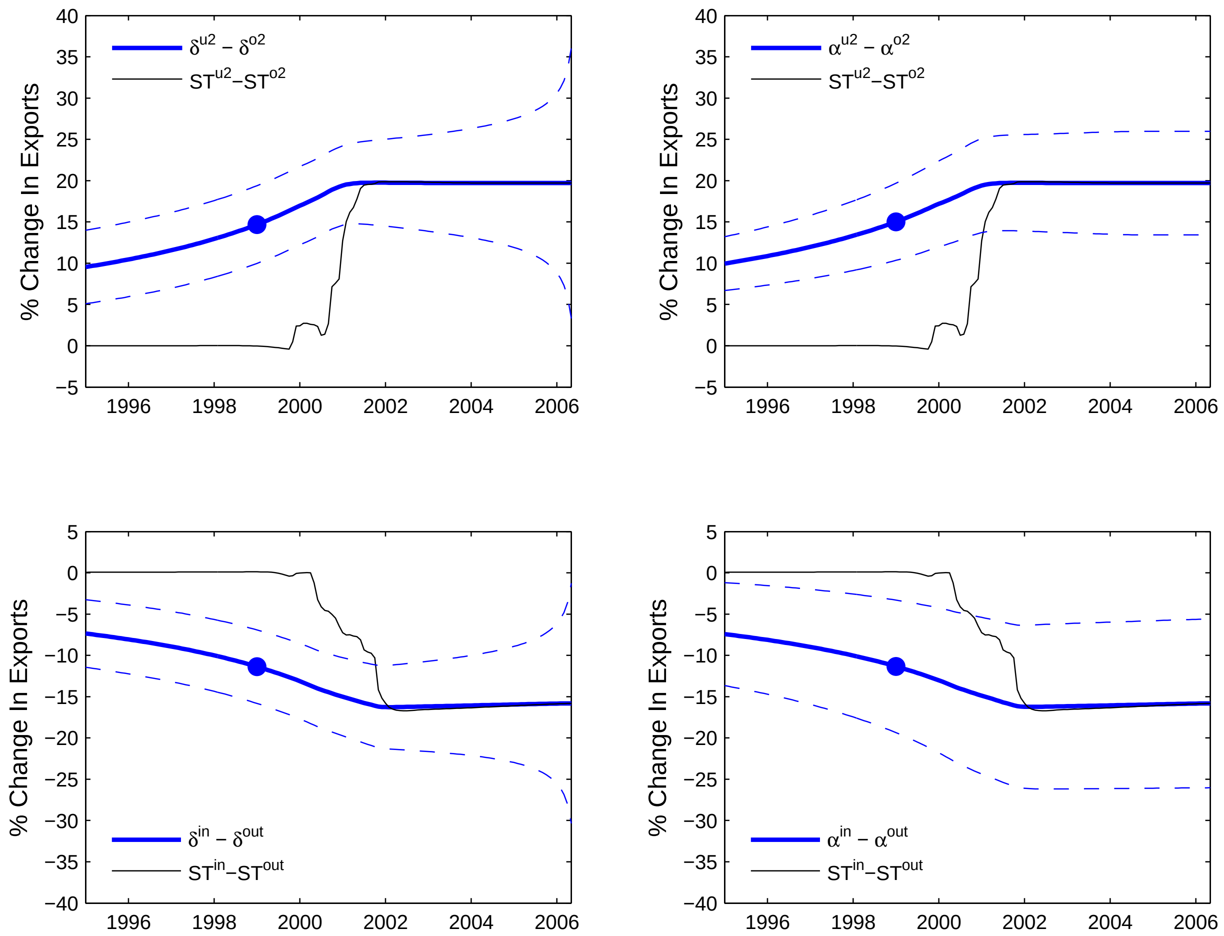


Figure 3: Dummy variables fitted to smooth transition paths. Top panels show results for U2 and O2 country pairs. Bottom panels show results for IN and OUT country pairs. Left hand side panels show results for pooled regression. Right hand side panels show results for heterogenous regression. Confidence bands are based on a 10% significance level.

Figure 3 summarizes results. The top left panel compares the difference $\delta^{u2} - \delta^{o2}$ to average smooth transition of U2 minus O2. The dot indicates the estimates obtained from a euro dummy which shifts in January 1999. Such a dummy implies a long-run effect of around 15 percent which appears significantly different from the 20 percent obtained for $ST_t^{u2} - ST_t^{o2}$ in May 2006 (see table 3 for estimates and standard errors). The reason for a lower estimate in the dummy model is that aggregate smooth transition starts after 1999 and is gradual. A model which minimizes squared errors between the transition path and a euro dummy therefore necessarily underestimates the long-run trade effect of the euro. A euro dummy which shifts in 2001 or later delivers basically the same long-run estimates as the smooth-transition specification because such a dummy bypasses the late and gradual adjustment. Some studies (see references in the introduction) estimate models with several consecutive euro dummies and thereby are likely to bypass a potential downward bias from the dummy specification.

The top right panel shows estimates $\alpha^{u2} - \alpha^{o2}$ obtained from regressions with sector- and country-specific euro dummies. Mean effects are very similar to those obtained from the pooled regression (see also table 3). One slight difference between $\alpha^{u2} - \alpha^{o2}$ and $\delta^{u2} - \delta^{o2}$ concerns confidence bands which are somewhat smaller for $\alpha^{u2} - \alpha^{o2}$. Apart from increasing estimation precision marginally, however, parameter heterogeneity appears to have very little impact on long-run estimates of the trade effect of the euro.

The bottom-left panel in figure 3 shows corresponding results for IN and OUT country pairs. Again, the pooled dummy specification indicates a considerably smaller long-run estimate of 11 percent in January 1999 relative to a long-run effect from aggregate smooth transition close to 16 percent. Interestingly, the latter estimate is close to the lower bound of a 90% confidence interval constructed around the former estimate such that $\delta^{in} - \delta^{out}$ differs significantly from -16 percent. Turning to sector- and country-specific regressions in the bottom-right panel, we find much larger confidence bands relative to the pooled regression. The finding suggests that, in some cases, unaccounted parameter heterogeneity would leave analysts overconfident regarding the magnitude of the average euro effect on trade.

# 7 Conclusions

We estimate the euro's effect on euro-area exports in different trade sectors and country pairs. Moreover, we analyze to what degree heterogeneity matters for estimating the aggregate trade effect of the euro. Our methodological contributions comprise sector- and country-specific heterogeneity in the elasticities of trade-costs on trade, smooth transition of long-lasting trade costs, and account of omitted trade costs and mismeasured multilateral resistance by means of the Kalman filter.

Due to a decrease in long-lasting trade costs, aggregate euro-area exports increase in the range of 15 to 25 percent relative to aggregate exports of European countries which are not member of the euro area. Most of the relative increase in euro-area exports takes place between the years 2000 and 2002. A new finding is the substantial amount of heterogeneity in the elasticities of trade costs on trade and in the adjustment of long-lasting trade costs to a new level. We disentangle three dimensions of transition, namely magnitude, speed, and timing, and estimate a high speed of transition at the level of individual sectors. However, aggregate adjustment is much more gradual and spread out because different sectors adjust at distinct times. The finding supports recent microfoundations of the euro's trade effect which predict the euro effect to unfold rapidly. When we fit a euro dummy to the estimated smooth-transition paths, the dummy specification indicates a considerably smaller trade effect of the euro as a consequence of country-pair and sector-specific timing.

While the finding that individual sectors adjust quickly but at different points in time is interesting in itself, future research is required to analyze the determinants of this behavior in more detail. Along these lines, it may be fruitful to augment the functional regression such that it can reflect variation in more sector characteristics relevant for sector-specific adjustment. Furthermore, future research could analyze the Kalman-filter extension of the gravity model more extensively.

## Acknowledgement

We thank Helge Berger, Sebastian Braun, Bartosz Maćkowiak, Volker Nitsch, Roman Liesenfeld, Alexandra Spitz-Oener, Jana Riedel, Albrecht Ritschl, Victor Steiner, and Till Müller for comments on a previous draft. We thank Albrecht Mengel for support in data handling and computational issues. Henning Weber thanks the Deutsche Forschungsgemeinschaft for financial support through the Collaborative Research Center 649 *Economic Risk*.

## References

Anderson, J. E., and E. van Wincoop (2003): "Gravity with Gravitas: A Solution to the Border Puzzle," *American Economic Review*, 93(1), 170–192.

——— (2004): "Trade Costs," *Journal of Economic Literature*, 42(3), 691–751.

Baier, S. L., and J. H. Bergstrand (2001): "The Growth of World Trade: Tariffs, Transport Costs, and Income Similarity," *Journal of International Economics*, 53, 1–27.

Baldwin, R., V. DiNino, L. Fontagne, R. A. D. Santis, and D. Taglioni (2008): "Study on the Impact of the Euro on Trade and Foreign Direct Investment," Economic Papers 321.

Baldwin, R. E. (2006a): "The Euro's Trade Effects," ECB Working Paper 594.

——— (2006b): *In or Out: Does It Matter? An Evidence-Based Analysis of the Euro's Trade Effects*. Centre for Economic Policy Research.

Baldwin, R. E., F. Skudelny, and D. Taglioni (2005): "Trade Effects of the Euro: Evidence from Sectoral Data," ECB Working Paper 446.

Baldwin, R. E., and D. Taglioni (2004): "Positive OCA Criteria: Microfoundations for the Rose Effect," unpublished manuscript.

——— (2006): "Gravity for Dummies and Dummies for Gravity Equations," NBER Working Paper 12516.

Bauwens, L., M. Lubrano, and J.-F. Richard (2000): *Bayesian Inference in Dynamic Econometric Models*. Oxford University Press: Oxford.

Berger, H., and V. Nitsch (2008): "Zooming Out: The Trade Effect of the Euro in Historical Perspective," *Journal of International Money and Finance*, 27(8), 1244–1260.

Broda, C., and D. E. Weinstein (2006): "Globalization and the Gains from Variety," *Quarterly Journal of Economics*, 121(2), 541–585.

Chang, Y., J. I. Miller, and J. Y. Park (2009): "Extracting a Common Stochastic Trend: Theories with Some Applications," *Journal of Econometrics*, 150(2), 231–247.

Chen, N., and D. Novy (2010): "Gravity, Trade Integration and Heterogeneity across Industries," University of Warwick Working Paper.

Cheng, I.-H., and H. J. Wall (2005): "Controlling for Heterogeneity in Gravity Models of Trade and Integration," *Federal Reserve Bank of St. Louis Review*, 87(1), 49–63.

DeNardis, S., and C. Vicarelli (2007): "The Impact of the Euro on Trade. The (Early) Impact is not so Large," in *Currencies and Globalization*, ed. by M. L. Ferrington, pp. 123–138. Nova Science Publishers, Inc.

Feenstra, R. (2003): *Advanced International Trade: Theory and Evidence*. Princeton University Press: Princeton.

Flam, H., and H. Nordström (2006a): "Euro Effects on the Intensive and Extensive Margins of Trade," CESIFO Working Paper 1881.

——— (2006b): "Trade Volume Effects of the Euro: Aggregate and Sector Estimates," Seminar Paper 746, Stockholm University.

Fratianni, M., and H. Kang (2006): "Heterogeneous Distance-Elasticities in Trade Gravity Models," *Economics Letters*, 90, 68–71.

Fuller, W. (1976): *Introduction to Statistical Time Series*. Wiley: New York.

Herwartz, H., and H. Weber (2005): "Exchange Rate Uncertainty and Trade Growth – A Comparison of Linear and Nonlinear (Forecasting) Models," *Applied Stochastic Models in Business and Industry*, 21(1), 1–16.

Jones, R. (1985): *Time Series Analysis with Unequally Spaced Data*, vol. 5. Handbook of Statistics.

Luukkonen, R., P. Saikkonen, and T. Teräsvirta (1988): "Testing Linearity against Smooth Transition Autoregressive Models," *Biometrika*, 75(3), 491–499.

Micco, A., E. Stein, and G. Ordonez (2003): "The Currency Union Effect on Trade: Early Evidence from EMU," *Economic Policy*, 18(37), 315–356.

Mongelli, F. P., E. Dorrucci, and I. Agur (2005): "What does European Institutional Integration tell us about Trade Integration?," ECB Occasional Paper Series 40.

Nitsch, V., and M. Pisu (2008): "Scalpel, Please! Dissecting the Euros Effect on Trade," unpublished manuscript, Freie Universität Berlin.

Novy, D. (2010): "International Trade and Monopolistic Competition without CES: Estimating Translog Gravity," CESifo Working Paper 3008.

Pesaran, M. H., and R. Smith (1995): "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels," *Journal of Econometrics*, 68, 79–113.

Phillips, P. C., and H. R. Moon (1999): "Linear Regression Limit Theory for Nonstationary Panel Data," *Econometrica*, 67(5), 1057–1111.

Recalde, M. L., and M. Florensa (2006): "Mercosur: Trade Creation or Trade Diversion? An Application of the Gravity Model and Kalman Filter," in *Trade, Integration and Economic Development: the EU and Latin America*, ed. by G. Tondl.

Sanz, F. (2000): "A Kalman Filter-Gravity Equation Approach to assess the Trade Impact of Economic Integration: The Case of Spain, 19861992," *Review of World Economics*, 136(1), 84–110.

Sanz, F., and J. M. Gil (2001): "An Assessment of the Agricultural Trade Impact of Spain's Integration into the EU," *Canadian Journal of Agricultural Economics*, 49(1), 53–69.

Silva, J., and S. Tenreyro (2010): "Currency Unions in Prospect and Retrospect," *Annual Review of Economics*, 2.

Teräsvirta, T. (1994): "Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models," *Journal of the American Statistical Association*, 89, 208–218.

White, H. (1980): "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica*, 48(4), 817–838.

# A Weighted Mean-Group Estimates

Mean-group estimation in dynamic panel models is considered by Pesaran and Smith (1995). In case of panel heterogeneity, the mean-group estimator measures marginal impacts for an average cross section member. In the spirit of Phillips and Moon (1999), mean-group estimation also guards against spurious inferential conclusions that might be attributed to single equation regressions with nonstationary data. As a possible statistical quantity characterizing the parameter heterogeneity one may consider the standard deviation of mean estimates.

**Construction of Weights:** Weights $w_k^{(s)}$ represent average relative exports in a given sector $k$ and conditional on trade relationship $s$ where the average is over the period 2001:06 to 2006:05,

$$w_k^{(s)} = \frac{\bar{y}_k^{(s)}}{\sum_s \bar{Y}^{(s)}} \quad , \quad \sum_s \sum_k w_k^{(s)} = 1 \ ,$$

where $\bar{Y}^{(s)} = \sum_k \bar{y}_k^{(s)}$ with $k = 1, \ldots, K$ and $s = 1, \ldots, S$.

**Coefficients and Standard Errors:** Let $\beta_k^{(s)}$ denote either a coefficient in $\mathbf{\Psi}_k^{(s)}$ or a single point in time of the transition path in a given sectors $k$ for a given country-pair $s$. We compute mean-group estimates of $\beta_k^{(s)}$ for the subset $s \in sub$ of country-pairs as

$$\beta^{sub} = \sum_k \sum_{s \in sub} \left( \frac{w_k^{(s)}}{\sum_k \sum_{s \in sub} w_k^{(s)}} \right) \beta_k^{(s)} \ .$$

We obtain a standard error for $\beta^{sub}$ as the square root of

$$V\left[\beta^{sub}\right] = \sum_k \sum_{s \in sub} \left( \frac{w_k^{(s)}}{\sum_k \sum_{s \in sub} w_k^{(s)}} \right)^2 V\left[\beta_k^{(s)}\right] \ ,$$

and estimate the moment $V\left[\beta_k^{(s)}\right]$ as

$$\widehat{V}\left[\beta_k^{(s)}\right] = \frac{1}{KS^{sub}} \sum_k \sum_{s \in sub} \left( \beta_k^{(s)} - \beta^{sub} \right)^2 \ . \tag{8}$$

Variable $S^{sub}$ denotes the number of country pairs in $sub$. In some cases, we also need the covariance to compute a standard error for the difference of mean-group estimates. We compute such a covariance as

$$Cov\left[\beta^{sub}, \beta^{sub'}\right] = \sum_{k} \sum_{s \in sub} \sum_{z \in sub'} \left(w_k^{(s)} w_k^{(z)}\right) Cov\left[\beta_k^{(s)}, \beta_k^{(z)}\right] ,$$

estimating the moment $Cov\left[\beta_k^{(s)}, \beta_k^{(z)}\right]$ as

$$\widehat{Cov}\left[\beta_k^{(s)}, \beta_k^{(z)}\right] = \frac{1}{K S^{sub} S^{sub'}} \sum_{k} \sum_{s \in sub} \sum_{z \in sub'} \left(\beta_k^{(s)} - \beta^{sub}\right)\left(\beta_k^{(z)} - \beta^{sub'}\right) \tag{9}$$

with $S^{sub} = S^{sub'}$. The variance and covariance estimators, $\widehat{V}\left[\beta_k^{(s)}\right]$ and $\widehat{Cov}\left[\beta_k^{(s)}, \beta_k^{(z)}\right]$, respectively, are the same for $s \in sub$, $z \in sub'$ and for all $k$. Notably, the estimators in (8) and (9) build upon the presumption that the respective moments are homogeneous over the involved cross sectional dimensions. Though such a presumption is hardly realistic one might expect that positive and negative approximation errors cancel at the aggregate level.

# B Smooth Transition Function

Smooth transition is a logistic cumulative distribution function (omit $s$ superscript and $k$ subscript), $[1 + \exp\{-\theta_1(t_\kappa/(T\sqrt{0.08\bar{3}}) - \zeta)\}]^{-1} = \kappa$ where $\kappa$ denotes percent of completed transition at date $t_\kappa$. Solve for $t_\kappa$,

$$t_\kappa = T\sqrt{0.08\bar{3}}\left(\zeta - \tfrac{1}{\theta_1}\ln(\tfrac{1}{\kappa} - 1)\right) .$$

The number of months needed to complete middle $(1 - 2\alpha)\%$ transition is the difference $t_{1-\alpha} - t_\alpha = 2T\sqrt{0.08\bar{3}}/\theta_1 \ln((1-\alpha)/\alpha)$. With $\alpha = .05, T = 137$ and $\theta_1 = 232.89$ the fastest 90% of transition happens within one month. The symmetry point of the transition function obtains with $\kappa = 0.5$ as $t_{0.5} = T\sqrt{0.08\bar{3}}\,\zeta$. Converting the lower and upper bound of $\zeta \in [0.30343, 3.186]$ into month delivers [12,126]. To approximate a dummy that kicks in at 1999:01, fix the symmetry point $\zeta = 1.2137$ and the transition speed $\theta_1 = 232.89$.

# C Kalman Recursions

Given the parameters of the state-space model in (2) to (5), $\mathbf{\Psi}_k^{(s)\prime}, \boldsymbol{\phi}^{(s)\prime}$, the Kalman filter provides sequentially linear projections for the dynamic system. The likelihood of the model is computed stepwise. In the following, reported estimates will have a second index reflecting the time point up to which data for the computations are collected. Such an extra index easily allows to discriminate between forecasts and updates. The analyst is assumed to have some guess concerning the initial states of the system $\left(\text{denoted}\lambda_{k,0|0}^{(s)}\right)$ and their variances $\left(P_{k,0|0}^{(s)}\right)$. The Kalman recursions for regression models with missing observations are given by the following steps (Jones (1985)):

1. Computation of a one step ahead forecast for the state and the associated variance:

$$\begin{aligned}\lambda_{k,t|t-1}^{(s)} &= \lambda_{k,t-1|t-1}^{(s)}\\ P_{k,t|t-1}^{(s)} &= P_{k,t-1|t-1}^{(s)} + h_k^{(s)}.\end{aligned}$$

2. The forecast of the state and observable explanatory variables are used to obtain a prediction for the dependent variable:

$$y_{k,t|t-1}^{(s)} = q_{it}^{(s)}\beta_{ik}^{(s)} + q_{jt}^{(s)}\beta_{jk}^{(s)} + (1-\sigma^{(s)})\left(\ln(\tau_{k,t}^{(s)}) + \lambda_{k,t|t-1}^{(s)}\right). \tag{10}$$

3. Comparing $y_{kt}^{(s)}$ and $y_{k,t|t-1}^{(s)}$ is feasible in case that $y_{kt}^{(s)}$ is observed. Then, the prediction error $u_{kt}^{(s)}$ with variance $W_{kt}^{(s)}$ is obtained as:

$$\begin{aligned}w_{kt}^{(s)} &= y_{kt}^{(s)} - y_{k,t|t-1}^{(s)}\\ W_{kt}^{(s)} &= (1-\sigma^{(s)})^2 P_{k,t|t-1}^{(s)} + g_k^{(s)}.\end{aligned}$$

4. The latter quantities contribute to the models' log likelihood with

$$l_{kt}^{(s)} = -0.5\ln(2\pi) - 0.5\left(u_{kt}^{(s)}\right)^2/W_{kt}^{(s)} - 0.5\ln W_{kt}^{(s)}. \tag{11}$$

5. The innovation $u_{kt}$ and its variance are used to update the current estimate of the state vector:

$$\begin{aligned}\lambda_{k,t|t}^{(s)} &= \lambda_{k,t|t-1}^{(s)} + P_{k,t|t-1}^{(s)}(1-\sigma^{(s)})u_{kt}^{(s)}/W_{kt}^{(s)}\\ P_{k,t|t}^{(s)} &= P_{k,t|t-1}^{(s)} + (1-\sigma^{(s)})^2\left(P_{k,t|t-1}^{(s)}\right)^2/W_{kt}^{(s)}.\end{aligned}$$

Note that the log likelihood function integrates over all time and sector-specific estimates $l_{kt}$

given in (11), i.e.

$$l = l\left(\mathbf{\Psi}_k^{s\prime}, \boldsymbol{\phi}^{s\prime}\right)' = \sum_k \sum_t l_{kt}.$$

In case a particular observation on $y_{kt}^{(s)}$ is missing, steps 3. and 4. are left out and the updating in step 5. becomes

$$\begin{aligned} \lambda_{k,t|t}^{(s)} &= \lambda_{k,t|t-1}^{(s)} \\ P_{k,t|t}^{(s)} &= P_{k,t|t-1}^{(s)}. \end{aligned}$$

# D Serial Correlation Tests

Serial correlation might easily be diagnosed by means of Portmanteau type test statistics exploiting the autocorrelation coefficients of the estimated model residuals $\hat{u}_{kt}^{(s)}$. To obtain an indication of serially correlated error terms which is robust under heteroskedasticity, however, we rather use the following auxiliary regression:

$$\hat{u}_{kt}^{(s)} = c + \kappa_1 \hat{u}_{kt-1}^{(s)} + \ldots + \kappa_h \hat{u}_{kt-h}^{(s)} + v_t,$$

where $c$ is an intercept term and $v_t$ a white noise disturbance. We test the null hypothesis $H_0$ : $\kappa_1 = \kappa_2 = \ldots = \kappa_h = 0$ by means of a Wald-test

$$\omega_h = \hat{\kappa}'(\mathrm{Cov}[\hat{\kappa}])^{-1}\hat{\kappa} \xrightarrow{d} \chi^2(h). \quad (12)$$

To implement the statistic in (12) we use the heteroskedasticity consistent covariance estimator for the estimated parameter vector $\hat{\kappa} = (\hat{\kappa}_1, \hat{\kappa}_2, \ldots, \hat{\kappa}_h)'$ (White (1980)). With respect to the choice of the lag order $h$ we consider tests on serial correlation at lag 1 and joint correlation at lags 1 to 12. The latter choices appear reasonable noting that monthly data enter our analysis.

# E Data Appendix

We adjust trade data by means of seasonal dummies. Merging data in value and in volume allows us to express exports in constant prices of 2000. To do so, we compute implicit unit-price deflators and use the average of the 12 price observations in 2000 to re-value volumes. Monthly industrial-production data comes from International Financial Statistics (IFS) of the IMF. Monthly exchange rates are market rates from IFS. Daily exchange-rate data used to compute exchange-rate volatility comes from the FED historical database.[23] The IFS indicators of real effective exchange rates based on unit labor costs in manufacturing represent the product of the index of the ratio of the relevant indicator (in national currency) for the country listed to a weighted geometric average of the corresponding indicators for 20 other industrial countries. Bilateral real exchange rates are computed as $rex = eP_{par}/P_{rep}$ where $e$ is reporter's currency in terms of partner's currency and $P_{rep}$ ($P_{par}$) denotes reporter's (partner's) producer price-index. For $rexus$ the partner country is the U.S.. Producer price-indices and the energy price-index are drawn from IFS. All indices are normalized to a base year 2000. We take natural logs of all series unless otherwise noted.

[23] http://www.federalreserve.gov/releases/h10/Hist/default1999.htm

Table 1: LR Specification Tests and Model Diagnostics

| $i,j$ | $\mathrm{LR}_d$ | SR | $\mathrm{LR}_f$ | AR1 | $I(1)$ | $\mathrm{LR}_X$ | $i,j$ | $\mathrm{LR}_d$ | SR | $\mathrm{LR}_f$ | AR1 | $I(1)$ | $\mathrm{LR}_X$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GER,FRA(U2) | 2.94 | 5.2 | 6240.5 | .35 | .98 | 17.7 | UK,GER (IN) | 5.79 | 4.6 | 5122.7 | .22 | .97 | 25.9 |
| GER,ITA(U2) | 3.74 | 4.8 | 6269.5 | .31 | .97 | 5.85 | UK,FRA (IN) | 1.85 | 4.9 | 3382.7 | .19 | .98 | 8.53 |
| GER,UK (OUT) | 4.35 | 4.1 | 4884.7 | .31 | .99 | 10.6 | UK,ITA (IN) | 6.68 | 3.8 | 3337.3 | .14 | .94 | 10.6 |
| GER,SWE(OUT) | 5.05 | 3.2 | 2260.9 | .32 | .93 | 9.04 | UK,SWE (O2) | 4.75 | 3.4 | 3029.2 | .27 | .93 | 3.02 |
| GER,DK (OUT) | 6.71 | 3.6 | 1668.5 | .20 | .98 | 10.5 | UK,DK (O2) | 5.27 | 2.9 | 1280.7 | .27 | .90 | 7.98 |
| FRA,GER(U2) | 5.71 | 7.5 | 6939.3 | .57 | .90 | 33.6 | SWE,GER(IN) | 0.02 | 3.8 | 3125.5 | .38 | .91 | 19.6 |
| FRA,ITA(U2) | 2.87 | 6.0 | 4635.4 | .39 | .94 | 29.2 | SWE,FRA(IN) | 0.90 | 3.6 | 1428.6 | .35 | .91 | 6.81 |
| FRA,UK (OUT) | 1.83 | 5.2 | 7747.5 | .37 | .95 | 52.7 | SWE,ITA(IN) | 2.10 | 3.5 | 1585.3 | .26 | 1.0 | 8.05 |
| FRA,SWE(OUT) | 5.72 | 3.7 | 2553.2 | .40 | .90 | 16.8 | SWE,UK (O2) | 0.11 | 3.4 | 1122.0 | .40 | .94 | 9.62 |
| FRA,DK (OUT) | 3.61 | 3.6 | 3619.9 | .34 | .87 | 21.6 | SWE,DK (O2) | 2.57 | 4.1 | 3129.7 | .26 | .95 | 11.8 |
| ITA,GER(U2) | 4.95 | 6.7 | 6418.9 | .46 | .87 | 18.9 | DK,GER (IN) | 1.41 | 4.9 | 3630.2 | .61 | .94 | 36.9 |
| ITA,FRA(U2) | 10.1 | 5.9 | 5658.9 | .74 | .80 | 20.6 | DK,FRA (IN) | 6.83 | 3.3 | 997.8 | .21 | .98 | 14.4 |
| ITA,UK (OUT) | 2.63 | 4.2 | 4769.6 | .37 | .83 | 15.7 | DK,ITA (IN) | 1.24 | 3.2 | 635.7 | .32 | 1.0 | 15.4 |
| ITA,SWE(OUT) | 1.70 | 3.3 | 1842.1 | .53 | .80 | 53.6 | DK,UK (O2) | 4.21 | 3.3 | 797.7 | .30 | .97 | 13.4 |
| ITA,DK (OUT) | 3.25 | 3.4 | 2251.0 | .41 | .84 | 18.4 | DK,SWE (O2) | 19.7 | 4.9 | 5587.4 | .20 | 1.0 | 5.94 |
| | | | | | | | crit 5% | 5.99 | - | 14.07 | .05 | - | 11.1 |
| | | | | | | | 10% | 4.60 | - | 12.02 | | - | 9.24 |

*Notes:* Estimated residuals of the observation equation (2) of the functional state-space model excluding exogenous control variables ($\boldsymbol{\psi}_1^{(s)} \neq 0, \boldsymbol{\gamma} = 0$) are diagnosed for stationarity ($I(1)$) and first order serial correlation (AR1). Diagnostics AR1 and $I(1)$ are frequencies of rejections of the null hypothesis over sectors. Serial correlation is diagnosed by means of a heteroskedasticity robust Wald statistic described in appendix D. Unit root tests are only performed for sectors where the number of missing observations is at most 5. Consequently, the frequencies of rejections of $H_0$ documented in the table refer to populations that depend on the trade relationship. The number of diagnostic unit root tests varies between 53 (Swedish exports to Italy) and 96. SR denotes the ratio of standard error estimates obtained when excluding unobserved variables $\lambda_{kt}^{(s)} = 0$ over standard error estimates from the homogeneous state-space model. $\mathrm{LR}_d$ and $\mathrm{LR}_f$ are LR statistics testing the smooth-transition homogeneous state-space model ($\boldsymbol{\psi}_1^{(s)} = 0$) against a euro-dummy homogeneous state-space model and the functional smooth-transition state-space model, respectively. Conditional on the functional state-space model, $\mathrm{LR}_X$ measures the explanatory content of five additional exogenous variables. 'U2', 'O2', 'OUT' and 'IN' classify trade relationships.

Table 2: Mean-Group Estimates

| | ALL | | U2 | | O2 | | IN | | OUT | |
|---|---|---|---|---|---|---|---|---|---|---|
| | coef. | std. | coef. | std. | coef. | std. | coef. | std. | coef. | std. |
| $\sigma$ | 5.345 | 0.077 | 5.494 | 0.168 | 5.402 | 0.230 | 5.314 | 0.095 | 5.090 | 0.113 |
| $c$ | 8.812 | 1.195 | 11.571 | 2.995 | 10.617 | 1.749 | 5.528 | 1.304 | 5.982 | 1.531 |
| $\beta_i$ | 0.871 | 0.097 | 0.914 | 0.121 | 0.306 | 0.149 | 1.043 | 0.193 | 0.821 | 0.172 |
| $\beta_j$ | 0.637 | 0.097 | 0.490 | 0.129 | -0.123 | 0.158 | 0.824 | 0.191 | 0.968 | 0.208 |
| $g$ | 0.469 | 0.064 | 0.334 | 0.085 | 0.712 | 0.052 | 0.551 | 0.124 | 0.576 | 0.145 |
| $h$ | 0.042 | 0.008 | 0.039 | 0.026 | 0.060 | 0.004 | 0.046 | 0.004 | 0.039 | 0.002 |
| $\theta_0$ | 0.008 | 0.015 | -0.001 | 0.009 | 0.046 | 0.010 | 0.031 | 0.020 | -0.003 | 0.046 |
| $\theta_1$ | 204.84 | 6.307 | 189.87 | 10.264 | 196.76 | 9.808 | 214.59 | 10.841 | 226 | 14.742 |
| $\zeta$ | 1.773 | 0.023 | 1.682 | 0.053 | 1.776 | 0.009 | 1.718 | 0.023 | 1.974 | 0.047 |
| $vol$ | 0.014 | 0.010 | 0.024 | 0.016 | 0.029 | 0.011 | -0.039 | 0.022 | 0.033 | 0.022 |
| $reer$ | -0.208 | 0.076 | -0.405 | 0.110 | 0.129 | 0.100 | 0.088 | 0.172 | -0.186 | 0.162 |
| $rex$ | 0.219 | 0.160 | 0.227 | 0.118 | 0.022 | 0.137 | 0.520 | 0.433 | 0.025 | 0.277 |
| $rexus$ | 0.131 | 0.033 | 0.050 | 0.049 | 0.251 | 0.054 | 0.208 | 0.047 | 0.180 | 0.081 |
| $en$ | -0.030 | 0.012 | -0.032 | 0.014 | -0.031 | 0.024 | -0.041 | 0.023 | -0.017 | 0.025 |

*Notes:* Estimates are based on the functional smooth-transition state-space model. See appendix A for computation of weighted-average coefficients 'coef.' and standard errors 'std.'. For the set of exogenous variables $vol, reer, rex, rexus$ and $en$ the table documents the weighted average of the respective element in $\boldsymbol{\gamma}_k^{(s)}$, multiplied by $(1 - \sigma^{(s)})$. These estimates thus reflect the trade elasticity of the respective exogenous variable.

Table 3: Long-Run Effects as Percentage Change in Exports

| | coef. | std. | | coef. | std. |
|---|---|---|---|---|---|
| $ST^{u2} - ST^{o2}$ in May 2006 | 19.703 | 3.803 | $ST^{in} - ST^{out}$ in May 2006 | -15.810 | 6.196 |
| $\delta^{u2} - \delta^{o2}$ in Jan. 1999 | 14.682 | 2.851 | $\delta^{in} - \delta^{out}$ in Jan. 1999 | -11.365 | 2.699 |
| $\alpha^{u2} - \alpha^{o2}$ in Jan. 1999 | 15.014 | 2.830 | $\alpha^{in} - \alpha^{out}$ in Jan. 1999 | -11.334 | 4.866 |

*Notes:* Statistics are long-run euro effects for exports in percent. See main text for the definition of variables. 'coef.' abbreviates coefficient estimate and 'std.' denotes the standard error. For details on computation see appendix A.