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# Article — Published Version Statistical identification in panel structural vector autoregressive models based on independence criteria

Journal of Applied Econometrics

**Provided in Cooperation with:** John Wiley & Sons

*Suggested Citation:* Herwartz, Helmut; Wang, Shu (2024) : Statistical identification in panel structural vector autoregressive models based on independence criteria, Journal of Applied Econometrics, ISSN 1099-1255, Wiley, Hoboken, NJ, Vol. 39, Iss. 4, pp. 620-639, https://doi.org/10.1002/jae.3044

This Version is available at: https://hdl.handle.net/10419/309470

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DOI: 10.1002/jae.3044

**RESEARCH ARTICLE** 

Revised: 5 December 2023

# Statistical identification in panel structural vector autoregressive models based on independence criteria **a**

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**Funding information** Deutsche Forschungsgemeinschaft, Grant/Award Number: HE 2188/8-2 and 2188/17-1

#### Summary

This paper introduces a novel panel approach to structural vector autoregressive analysis. For identification, we impose independence of structural innovations at the pooled level. We demonstrate robustness of the method under cross-sectional correlation and heterogeneity through simulation experiments. In an empirical application on monetary policy transmission in the Euro area, we find that bond spreads rise significantly after an unexpected monetary tightening. Furthermore, the central bank responds to offset effects of adverse financial shocks. Additionally, we document sizable heterogeneity in country-specific output responses.

#### **KEYWORDS**

Euro area, financial conditions, independent component analysis, monetary policy, panel data, structural VAR

# **1** | INTRODUCTION

Structural VARs (SVARs) have become indispensable tools for macroeconometricians and policymakers for assessing effects of structural shocks on macroeconomic aggregates. Identification methods play an essential role in SVAR analyses and can be broadly categorized as theory-based, instrument-based, and statistical approaches. While statistical identification methods seem attractive in situations with limited theoretical or institutional knowledge, or a lack of external instruments, their finite-sample performance in macroeconomic applications might face challenges due to the short time spans of available data. To address this, our paper proposes a panel approach that builds upon the assumption of independent pooled structural shocks. This methodological contribution places us at the intersection of statistical identification in SVARs and its extension to the panel context (see Canova & Ciccarelli, 2013, and Kilian & Lütkepohl, 2017, for comprehensive literature reviews, respectively). As an important field of application, we investigate the transmission mechanisms of monetary policy (MP) and financial shocks among fourteen Euro area (EA) member states, within a relatively short time period starting with the introduction of the common currency in 1999 (Corsetti et al., 2021; Georgiadis, 2015; Peersman, 2004).

Identification in SVARs typically relies on economic theory and institutional knowledge that can be used to develop exclusion restrictions (e.g., Blanchard & Quah, 1989; Sims, 1980), sign restrictions (e.g., Faust, 1998; Uhlig, 2005), or instruments for structural shocks (Mertens & Ravn, 2013; Stock & Watson, 2012). However, a potential drawback of theory-based identification, as highlighted by Uhlig (2005), is the risk of conflating assumptions with empirical conclusions. In addition, the availability of valid and sufficiently strong external instruments is not always guaranteed. To address these challenges, a branch of SVAR analysis has emerged, exploring statistical properties of the data-generating process. This involves leveraging heteroskedasticity (see, e.g., Lewis, 2021; Rigobon & Sack, 2003) or imposing statisti-

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made. © 2024 The Authors. Journal of Applied Econometrics published by John Wiley & Sons Ltd. cal independence among the shocks (see, e.g., Anttonen et al., 2023; Gouriéroux et al., 2017; Lanne et al., 2017; Lanne & Luoto, 2021). While these statistical identification approaches have yielded fruitful results and provided interesting economic insights, they face two important limitations. First, statistical identification alone does not guarantee the interpretability of the outcomes from an economic perspective. Second, these methods may suffer from a high estimation uncertainty when sample information is limited. Addressing these concerns, especially in cases of macroeconomic variables measured at low frequency or over short periods, a panel data approach becomes attractive. This is particularly relevant when research questions pertain to cross-sections sharing similar institutions and regulations, such as the G7, the OECD, or the EA. By pooling data across multiple cross-sectional members, the panel approach mitigates data scarcity at the individual level, allowing for improved statistical identification performance through the combination of both data dimensions, namely, "length" (denoted by T) and "width" (denoted by N). For example, panel data analysis has been extensively employed to assess hypotheses like purchasing power parities through panel unit root and cointegration tests (Breitung & Pesaran, 2008; Breitung & Westerlund, 2013; Taylor & Taylor, 2004).

Applied panel (S)VARs often rely on reduced-form specifications or zero and sign restrictions for structural identification (Canova & Ciccarelli, 2013). For instance, Pedroni (2013) specifies a panel SVAR model with flexible loadings, identifying structural shocks through a Cholesky scheme. Meanwhile, Georgiadis (2015) identifies MP shocks through sign restrictions, scrutinizing their transmission in EA economies. Unlike sign or zero restrictions, adapting statistical identification procedures to panel models is challenging, as informative patterns of mixed or heteroskedastic distributions may not universally apply to all panel members. Additionally, strong distributional assumptions for independent shocks, enabling parametric methods for independent component analysis (ICA), may lack general applicability. In contrast, methods derived under the principle of Hodges-Lehmann (HL) estimation (Dufour, 1990; Hodges & Lehmann, 2006)—minimizing statistics from non-parametric independence tests (as provided, for instance, by Bakirov et al., 2006; Genest et al., 2007; Székely et al., 2007)—may benefit from less stringent distributional assumptions. This approach has found successful application in single monetary policy SVAR models with both small and large dimensions (Herwartz, 2018; Herwartz & Wang, 2023).

In this paper, we advocate for the utilization of HL estimation for statistical identification in panel SVAR models. We articulate the conditions necessary to establish the identifiability of structural shocks at the pooled level and discuss their implications at the individual cross-section level. Through comprehensive simulation-based evidence, we underscore the performance enhancement achieved through pooling, taking into consideration key panel data features, such as cross-sectional correlations and heterogeneity. We compare the proposed HL estimator with other independence-based identification approaches, including (pseudo) ML and GMM estimators (see Gouriéroux et al., 2017, and Keweloh, 2021; Lanne & Luoto, 2021, respectively). To shed light on the transmission of monetary policy in the EA, empirical results for a panel of 14 EA member states are presented and compared with outcomes from an EA-wide model.

Our findings suggest that cross-sectional pooling substantially improves statistical identification in macroeconomic panels with a small time series dimension. This is especially pertinent given that HL estimation based on non-parametric independence criteria proves more robust under cross-sectional correlations and heterogeneity compared to alternative procedures. Concerning the effects of MP in the EA, our results indicate that MP shocks have sizable and persistent effects on real output at the weighted mean group (MG) level. A contractionary shock resulting in a 25 bps interest rate hike leads to a reduction in real GDP of 0.2% and 0.25% at horizons of 2 and 5 years, respectively. Bond spreads react immediately and significantly to MP surprises, and the European Central Bank (ECB) systematically responds to an exogenous tightening of financial conditions to offset potential adverse effects. Evidently, a comprehensive understanding of the contemporaneous interaction between MP and financial conditions is crucial for estimating the real effects of MP shocks within the EA (see Caldara & Herbst, 2019, for similar evidence for the United States). Moreover, unconventional policies are found to be as effective as conventional policy tools. Regarding the important aspect of EA heterogeneity (e.g., Corsetti et al., 2021; Peersman, 2004), our estimated country-specific output responses to MP shocks align strikingly with previous findings documented in fig. 5 of Corsetti et al. (2021), where MP shocks are partially identified based on high-frequency instruments.

The remainder of the paper is structured as follows: Section 2 outlines the proposed HL estimator for independence-based identification within a panel data context. Section 3 provides simulation-based evidence, while Section 4 presents empirical results on the effects of MP within the EA. Section 5 concludes. Appendix S1 provides a stylized illustration of the identification scheme (Section S1), further simulation results (Sections S2 and S4), and materials that supplement the empirical analysis (Section S3, data description, reduced-form and structural diagnostics, bootstrap inference, and additional impulse responses).

## 2 | METHODOLOGY

This section introduces a statistical identification approach in panel SVAR models. We state the panel VAR model in both its reduced and structural forms, along with identifying assumptions and discuss the impact of cross-sectional correlation and heterogeneity on uniqueness of the structural model. Moreover, we outline Hodges-Lehmann (HL) estimation principles for the structural model.

#### 2.1 | Model specification and identifying assumptions

Conditional on available presample values, the K-dimensional panel SVAR model of order  $P_i$  for member i is given by

$$y_{it} = v_i + A_{i1}y_{it-1} + A_{i2}y_{it-2} + \dots + A_{iP_i}y_{it-P_i} + u_{it},$$
(1)

$$= v_i + A_{i1}y_{it-1} + A_{i2}y_{it-2} + \dots + A_{iP_i}y_{it-P_i} + D_i\xi_{it},$$
(2)

$$\iff A_i(L)y_{it} = v_i + D_i\xi_{it}, \ t = 1, \dots, T, \ i = 1, \dots, N,$$
(3)

where  $y_{it} = (y_{it}^{(1)}, \dots, y_{it}^{(K)})'$  represents the  $K \times 1$  vector of observable variables and  $A_{ip}$ ,  $p = 1, \dots, P_i$ , are  $K \times K$  autoregressive parameter matrices. The corresponding lag polynomial is defined as  $A_i(L) = I - A_{i1}L - \dots - A_{iP_i}L^{P_i}$  and the fixed effects specific to cross-section *i* are collected by vector  $v_i$ . Under the assumption of causal cross-sectional dynamics, det $(A_i(z)) \neq 0, \forall |z| \leq 1, z \in \mathbb{C}$  and the reduced-form residuals  $u_{it}$  exhibit a zero mean and a cross-section-specific covariance matrix, that is,  $u_{it} \sim (0, \Omega_i)$ . The vector of structural shocks in Equation (3), denoted as  $\xi_{it} = (\xi_{it}^{(1)}, \dots, \xi_{it}^{(K)})'$ , has a mean of zero and an identity covariance matrix, that is,  $\xi_{it} \sim (0, I_K)$ . These structural shocks are linked to the reduced-form system through a nonsingular  $K \times K$  structural mixing matrix  $D_i$ , satisfying  $D_i D'_i = \Omega_i$ .

It is widely recognized in the SVAR literature that the matrix  $D_i$  remains unidentified without additional assumptions. To focus more sharply on the identification problem, we introduce  $\Gamma_i$ , a diagonal matrix collecting the marginal variances of the reduced-form residuals, and  $G_i$ , a baseline decomposition (e.g., a lower triangular matrix) of the correlation matrix  $\tilde{\Omega}_i$ , such that  $G_i G'_i = \tilde{\Omega}_i = \Gamma_i^{-1/2} \Omega_i \Gamma_i^{-1/2}$ . By consistently estimating the parameters in the reduced-form model (1), including the covariance matrix, we can obtain the non-structural orthogonalized residuals  $\tilde{\xi}_{it} = G_i^{-1} \Gamma_i^{-1/2} u_{it}$ . The identification problem can then be framed as solving the system of equations given by

$$\tilde{\xi}_{it} = Q_i \xi_{it},\tag{4}$$

where  $Q_i$  is an orthonormal matrix satisfying  $Q_i Q'_i = I_K$ . It can be verified that  $\tilde{\xi}_{it} \sim (0, I_K)$  and  $D_i = \Gamma_i^{1/2} G_i Q_i$ .

While the structural mixing matrix  $D_i$  in (3) may exhibit cross-sectional variation, it is often reasonable to impose certain degrees of homogeneity on the structural implications. In cases where profiles of instantaneous transmission of structural shocks  $\xi_t$  to orthogonalized residuals  $\tilde{\xi}_{it}$  apply to the entire cross-section (i.e.,  $Q_i = Q$  for all *i*), statistical identification performance can benefit from cross-sectional pooling and the combination of both data dimensions (i.e., "length" *T* and "width" *N*). Hence, we make the following distributional assumptions to establish the identifiability of *Q* and consequently  $D_i$ .

**Assumption 1.** Let  $\tau = 1, ..., NT$  denote a sequence of ordered indices reflecting the Cartesian product of the sets of cross-sectional (i = 1, ..., N) and time indices (t = 1, ..., T). It holds for random vectors  $\tilde{\xi}_{\tau} = (\tilde{\xi}_{\tau}^{(1)}, ..., \tilde{\xi}_{\tau}^{(K)})'$  and  $\xi_{\tau} = (\xi_{\tau}^{(1)}, ..., \xi_{\tau}^{(K)})'$  in (4) that

$$\tilde{\xi}_{\tau} = Q\xi_{\tau} \text{ and } \xi_{\tau}^{(k)} \sim \varphi^{(k)}(0,1), k \in \{1, \dots, K\},$$
(5)

where  $\varphi^{(k)}$  is a centered and standardized univariate distribution and at most one of  $\varphi^{(k)}$  is a Gaussian distribution.

**Assumption 2.** The components in the vector of structural shocks  $\xi_{\tau}$  are mutually independent.

**Theorem 1.** Under Assumptions 1 and 2, the orthogonal mixing matrix Q is identified up to right-multiplication by  $\Lambda P$ , where  $\Lambda$  is a diagonal matrix with diagonal elements being  $\pm 1$  and P is a permutation matrix. In other words, Q is identifiable up to column permutations and sign flips.

Theorem 1 follows directly from the characterization theorem of Darmois-Skitovich for Gaussian linear forms (see also Th.11 in Comon, 1994). A proof is provided in Appendix A.

While the indeterminacy of column permutations and signs can be removed by imposing mechanical restrictions,<sup>1</sup> statistical identification alone does not necessarily provide a sound economic interpretation of the resulting shocks. To render the shocks meaningful in an economic sense, additional reasoning based on economic theory and institutional background is necessary. A comprehensive discussion of the so-called shock labeling can be found in Herwartz and Lütkepohl (2014). Recently, Herwartz and Wang (2023) have demonstrated that carefully designed sign restrictions can effectively constrain the parameter space of the matrix Q to a subspace that exclusively encompasses shocks with sound economic interpretations.

Given that our novel identification approach aims to identify panel SVAR models through cross-sectional pooling, it becomes crucial to comprehend the implications of the identifying assumptions at the level of individual cross-sections. Furthermore, panel data introduces specific considerations that necessitate careful attention. Next, we explicitly tackle these concerns to provide a comprehensive understanding of our approach.

#### 2.2 | Statistical identification in panel SVAR models

#### 2.2.1 | Independence at the pooled level

To enhance the performance of statistical identification in panel SVAR models through cross-sectional pooling, this study employs identifying assumptions that deviate from those commonly used for identifying single SVAR models. Our approach distinguishes itself in two key aspects. First, it imposes a stronger condition of independence at the pooled level, which differs from the typical requirement of independence at each individual cross-sectional level

*Remark* 1. The independence assumption at the pooled level, as stated in Assumption 2, is stronger than the independence assumption at each cross-sectional level, which asserts that the components in  $\xi_{it}$  are mutually independent for all i = 1, ..., N.

To illustrate this, let us assume that *N* is even and the *k*-th structural shock for cross-section *i* at time *t* is generated as follows:

$$\xi_{it}^{(k)} = \kappa_i \eta_{it}^{(k)}, \, k = 1, \, \dots, K, \tag{6}$$

where  $\kappa_i$  is a scalar variable common to all shocks within cross-section *i* and  $\eta_{it}^{(k)}$  is independent from  $\eta_{it}^{(k')}$  for  $k \neq k'$ . While within the same cross-section  $\xi_{it}^{(k)}$  is independent of  $\xi_{it}^{(k')}$ , at the pooled level,  $\xi_{\tau}^{(k)}$  may not be independent of  $\xi_{\tau}^{(k')}$ . For example, let  $\eta_{it}^{(k)}$  follow an exponential distribution for all *k*, that is,  $\eta_{it}^{(k)} \stackrel{iid}{\sim} Exp(\lambda)$  with  $\lambda > 0$ . Furthermore, define  $\kappa_i = 1$  if *i* is even and  $\kappa_i = -1$  if *i* is odd. It can be verified that the marginal distribution of the pooled shock  $\varphi^{(k)}$  is a symmetric exponential mixture with  $\mathbb{P}\left(\xi_{\tau}^{(k)} > 0\right) = 1/2$  and  $E\left[\xi_{\tau}^{(k)}\right] = 0$ . However, for  $k \neq k'$ , the corresponding conditional probability is  $\mathbb{P}\left(\xi_{\tau}^{(k)} > 0\right) = 1$  and conditional expectation  $E\left[\xi_{\tau}^{(k)}|\xi_{\tau}^{(k')} > 0\right] = 1/\lambda > 0.^2$ 

It is worth noting that when only a subset of the shocks satisfies the assumption of independence while others do not, Cardoso (1998) demonstrates that the mutually independent shocks can still be uniquely identified. The framework of HL estimation proposed in this study allows for addressing partial identification in the presence of dependent shocks by appropriately adjusting the employed independence test. This topic has recently been discussed in Herwartz and Wang (2023).

<sup>&</sup>lt;sup>1</sup>Due to this indeterminacy, the model is sometimes referred to as "locally identified." One approach to achieving global identification is by selecting the column signs and ordering such that the diagonal elements of matrix Q are positive, and the trace of Q is maximized among all K! possible column orderings. Alternative methods have been explored, which involve imposing specific constraints on the structural mixing matrix D derived from Q (see, e.g., Lanne et al., 2017).

<sup>&</sup>lt;sup>2</sup>In this illustration, we have disregarded the assumptions about the mean and variance of the structural shocks, as they do not play a role in the current argument. It is worth noting that a similar problem related to co-heteroskedasticity is discussed in Montiel Olea et al. (2022).

The second aspect that distinguishes our approach is the imposition of cross-sectional homogeneity on the orthogonal rotation matrix *Q*.

*Remark* 2. The panel SVAR approach proposed in this work is based on the assumption of cross-sectional (and temporal) invariance of the rotation matrix *Q* in (4).

While this assumption may seem restrictive, it is essential to note that the structural mixing matrix  $D_i$  in (4) provides flexibility in terms of cross-section-specific marginal variances and correlations, characterized by  $\Gamma_i$  and  $G_i$ , respectively. The approach is primarily restrictive in terms of the contemporaneous causal direction, which is captured by the common rotation matrix Q.<sup>3</sup> This consideration becomes particularly relevant when panel members are subject to similar legislative or regulatory restrictions, such as belonging to the same currency union, or share other institutional similarities. It is worth mentioning that this assumption is implicit in some theory-based identifications where economic theory is assumed to hold for all panel members. For instance, in the case where identification is achieved by imposing a recursive scheme, the variable ordering requires careful justification that should apply consistently across the entire cross-section. In such recursive systems, where  $D_i$  is lower triangular, the matrix Q is constrained to be an identity matrix for all panel sections.

However, the economic implications of a cross-sectionally homogeneous *Q* matrix should be carefully investigated and justified based on economic theory and institutional knowledge. If there are compelling reasons to believe that specific transmission patterns exist within certain subsets of the cross-sections (e.g., large vs. small economies) or during specific time periods, it is possible to estimate different rotation matrices for different pools constructed as well-defined subsamples. This allows for greater cross-sectional and temporal flexibility in the transmission mechanism. Furthermore, if the assumption of a common rotation is violated for certain panel members, the recovered structural shocks for those members cannot be statistically independent under the assumption of non-Gaussianity. This is due to the uniqueness of linear forms of non-Gaussian independent variables. Diagnostic analysis can be conducted using powerful tools available for testing independence (Bakirov et al., 2006; Genest et al., 2007; Matteson & Tsay, 2017).

To assess the robustness of the proposed approach against potential deviations from the assumption of a common rotation matrix, we perform a Monte Carlo experiment in Section 3.2. In the empirical application of this study, we thoroughly examine the implications of a common rotation by comparing cross-section-specific structural outcomes with those reported in a benchmark study (Corsetti et al., 2021) and in an aggregate (EA-wide) model. Additionally, we present in Section S3.3 comprehensive diagnostic evidence to support the statistical identifying assumptions. Furthermore, to accommodate temporal flexibility, we apply the proposed panel SVAR approach to subsample periods characterized by both conventional monetary policies and unconventional measures.

#### 2.2.2 | Cross-sectional correlation and heterogeneity

When considering structural identification in macroeconomic panel data models, it is crucial to account for two important data features. First, the same type of structural shock may exhibit cross-sectional correlation. Second, cross-sectional heterogeneity can arise from the idiosyncratic characteristics of specific panel members.

The cross-sectional correlation between specific shocks from different panel members, denoted as  $\xi_{it}^{(k)}$  and  $\xi_{jt}^{(k)}$ ,  $i \neq j$ , manifests as serial correlation in  $\xi_r^{(k)}$ . In extreme cases, one might consider the presence of a common shock, where  $\xi_{1t}^{(k)} = \dots = \xi_{Nt}^{(k)}$ . However, such cross-sectional correlation patterns do not violate the independence Assumption 2 imposed on distinct shocks, that is,  $\xi_r^{(k)}$  independent of  $\xi_r^{(k)}$  for  $k \neq k'$ . Thus, the identifiability of the system remains intact. Moreover, since the sequence of structural shocks is typically assumed to be generated from a white noise process, most ICA routines, such as the non-Gaussian ML estimator of Lanne et al. (2017), remain consistent.<sup>4</sup> Nevertheless, tools for testing the null hypothesis of independence may experience efficiency loss, and the performance enhancement of statistical identification achieved by combining both data dimensions may not reach its full potential. Matters of contemporaneous cross-sectional dependencies have been extensively discussed in various empirical and theoretical analyses of macroeconomic panel data

<sup>&</sup>lt;sup>3</sup>For a detailed interpretation of the orthogonal matrix Q as a rotation transformation (or reflection, depending on the orientations of the bases), we refer the reader to Herwartz and Wang (2023).

<sup>&</sup>lt;sup>4</sup>For a fixed number of panel sections *N*, it can be verified that the sequence of structural shocks  $\xi_{\tau}$  is strong  $\alpha$ -mixing. This property allows for the establishment of laws of large numbers and central limit theorems for statistics related to  $\xi_{\tau}$ , even in the presence of considerable serial correlation (see, e.g., White & Domowitz, 1984). It is widely recognized that ML estimation remains consistent and asymptotically normal for mixing processes (see, e.g., Levine, 1983).

Regarding cross-sectional heterogeneity, it is worth noting that pooling samples obtained from orthogonalized reduced-form residuals homogenizes the first two moments of the shocks. The distributional heterogeneity of shocks can be empirically tested, for instance, using classical Kolmogorov-Smirnov tests. In general, such cross-sectional heterogeneity does not impair the ICA approach for identifying independent components at the pooled level. Nevertheless, there are special cases, as illustrated in the previous section, where distinct shocks from different cross-sections exhibit coexisting cross-sectional distributional properties. Such cross-sectional "co-heterogeneity" in the shock distribution renders the shocks  $\xi_{\tau}^{(k)}$  and  $\xi_{\tau}^{(k')}$  for  $k \neq k'$  dependent at the pooled level, thus violating identifying Assumption 2. Diagnostic tests for the independence of components in  $\xi_{\tau}$  can be applied to examine such patterns of co-heterogeneity.

Given these considerations regarding the specific features of panel data, it becomes crucial for the chosen ICA approach to exhibit favorable performance in finite samples, especially when dealing with serial correlation and distributional heterogeneity. In practice, relying on pre-specified probability density functions through parametric or semi-parametric approaches, such as the non-Gaussian ML approach proposed by Lanne et al. (2017) or the PML approach introduced by Gouriéroux et al. (2017), may carry a risk of misspecification. Consequently, analysts may prefer less restrictive approaches, like GMM methods presented in Lanne and Luoto (2021) and Keweloh (2021), that incorporate higher order cross-moment conditions such as co-skewness and co-kurtosis. Another alternative is the non-parametric approach known as Hodges-Lehmann estimation, which utilizes independence tests for identification (Herwartz, 2018).<sup>5</sup> Among these approaches, simulation results provided by Herwartz (2018) and Herwartz and Wang (2023) and in Sections 3.1, S2, and S4 of this work demonstrate the robustness of HL estimation under a wide range of data-generating processes and diverse distributional features. Considering these compelling results, we believe that HL estimation is highly suitable for structural identification in panel SVAR models. We next provide a brief description of this approach.

#### 2.3 | Hodges-Lehmann estimation based on independence criteria

As a first step, given its specification and conditioning on presample values, the parameters in the reduced-form (1) are individually estimated using least squares (LS) for different panel members.<sup>6</sup> These estimates, including the reduced-form AR parameters  $\hat{A}_{ip}$ ,  $p = 1, 2, ..., P_i$ , and covariance matrices  $\hat{\Omega}_i$ , are then used to retrieve the residual vector  $\hat{u}_{it}$ , the diagonal matrix containing the marginal variances  $\hat{\Gamma}_i$ , and the lower triangular Cholesky factor of the correlation matrix  $\hat{G}_i$ . From these quantities, the vector of orthogonalized residuals is obtained as  $\hat{G}_i^{-1}\hat{\Gamma}_i^{-1/2}\hat{u}_{it}$ .

To identify the independent structural shocks, we express the orthogonal matrix *Q* as a product of Givens rotation matrices, parameterized by rotation angles collected in the  $K(K - 1)/2 \times 1$  vector  $\theta$ .<sup>7</sup>

For a given choice of  $\theta$ , we define a candidate structural mixing matrix  $D_{\theta,i} := \hat{\Gamma}_i^{1/2} \hat{G}_i Q_{\theta}$  and the implied vector of structural shocks  $\xi_{\theta,it} := D_{\theta,i}^{-1} \hat{u}_{it}$ . These candidate shocks are then pooled to form the sample defined as

$$\mathcal{A}_{\theta}^{(N)} := \left\{ \{\xi_{\theta, it}\}_{t=1}^{T} \right\}_{i=1}^{N}.$$
(8)

The proposed panel SVAR identification method aims to minimize the mutual dependence among the components in  $\mathcal{A}_{\theta}^{(N)}$  with respect to  $\theta$ , that is,

$$\hat{\theta} := \arg\min_{\theta} \left\{ \text{Mutual dependence of the } K \text{ components in } \mathcal{A}_{\theta}^{(N)} \right\}.$$

<sup>7</sup>For instance, in the trivariate case, one has

$$Q_{\theta} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta_1) & -\sin(\theta_1) \\ 0 & \sin(\theta_1) & \cos(\theta_1) \end{bmatrix} \begin{bmatrix} \cos(\theta_2) & 0 & -\sin(\theta_2) \\ 0 & 1 & 0 \\ \sin(\theta_2) & 0 & \cos(\theta_2) \end{bmatrix} \begin{bmatrix} \cos(\theta_3) & -\sin(\theta_3) & 0 \\ \sin(\theta_3) & \cos(\theta_3) & 0 \\ 0 & 0 & 1 \end{bmatrix},$$
(7)

where  $\theta_j \in [0, 2\pi), j = 1, ..., K(K - 1)/2$ .

<sup>&</sup>lt;sup>5</sup>Generalizations of the restrictive non-Gaussian ML approach have also been attempted from a Bayesian perspective. These include utilizing a Dirichlet process mixture to specify the shocks (Braun, 2021) or employing a skewed generalized *t*-density (Anttonen et al., 2023).

<sup>&</sup>lt;sup>6</sup>Properties of the LS estimator for parameters in VAR models are discussed in Section 2.3 of Kilian and Lütkepohl (2017). Canova and Ciccarelli (2013) discuss alternative approaches for estimating reduced-form models across a wider range of specifications.

The identified cross-sectional-specific structural mixing matrix is then obtained as

$$\hat{D}_i := D_{\hat{\theta},i} = \hat{\Gamma}_i^{1/2} \hat{G}_i Q_{\hat{\theta}}.$$
(9)

Recognizing that the linear mapping from the structural to reduced-form disturbances can be represented by an orthogonal rotation (*Q*), a shearing transformation (*G*), and a stretching/squeezing transformation ( $\Gamma^{1/2}$ ), the stylized bivariate example depicted in Figure S1.1 in Section S1 offers a visual illustration of our proposed approach. It demonstrates how our approach addresses the inherent trade-off between model flexibility and parsimony, which is often a key consideration in the analysis of macroeconomic panel data.

To measure the mutual dependence among the components in  $\mathcal{A}_{\theta}^{(N)}$ , we employ a set of test statistics from non-parametric independence tests. The choice of  $\hat{\theta}$  is made to minimize the evidence against the null hypothesis of independence, lending it the interpretation of a HL estimator (Dufour, 1990; Hodges & Lehmann, 2006). As a benchmark dependence measure, we employ a test based on the distance covariance (dCov) statistic introduced by Székely et al. (2007), denoted as  $\mathcal{T}$ . It has been demonstrated by Matteson and Tsay (2017) to exhibit favorable power characteristics across a wide range of violations of the null hypothesis. We further utilize the Cramér-von-Mises (CvM) distance introduced by Genest et al. (2007), denoted as  $\mathcal{B}$ , for robustness analysis and additional diagnostic testing.<sup>8</sup>

#### **3 | MONTE CARLO ANALYSIS**

In this section, we assess the simulation performance of the proposed statistical identification approach in panel SVAR models. Previous Monte Carlo studies have examined the effectiveness of statistical identification using non-parametric independence tests in single SVAR models (e.g., Herwartz, 2018; Herwartz & Wang, 2023). For example, based on a set of carefully selected shock distributions, Herwartz and Wang (2023) show that the HL approach performs well even in scenarios where the structural shocks are "almost" Gaussian. Additionally, Matteson and Tsay (2017) demonstrate through simulations that ICA based on the dCov statistic T outperforms other prominent ICA methods, such as FastICA (Hyvärinen & Oja, 1997), under various data-generating distributions.

We conduct the first set of experiments in Section 3.1 to investigate the extent to which the performance enhancement through pooling translates to panel data with substantial cross-sectional correlations and heterogeneity. We also compare the proposed approach with alternative independence-based identification methods, such as GMM and PML. The second set of experiments in Section 3.2 explores the impact of violating the strict assumption of a common rotation matrix on the performance of the suggested approach. We also consider the presence of a cross-sectionally common shock to mimic the case of a monetary union, which is relevant for the empirical analysis of the EA.

#### 3.1 | Robustness of Hodges-Lehmann estimation in panel data

We simulate a pair of independent components (K = 2) generated with equal probabilities (drawn with replacement) from 18 distributions. As shown in the left-hand side panel of Figure 1, these distributions include uniform (distribution 1), Student's *t* with 3 and 5 degrees of freedom (2 and 4), exponential (12), Gaussian mixtures (symmetric: 5–6 and 8–11; asymmetric: 13–18), and mixtures of exponential distributions (3 and 7). The alternative distributions encompass a wide range of stochastic origins that may be relevant in empirical practice, such as symmetric versus asymmetric shocks, unimodal versus multimodal, and leptokurtic versus platykurtic distributions. The independent components generated from all data-generating distributions are centered and standardized to have mean zero and unit variance. After generation, the independent components are mixed using a common orthogonal matrix *Q* drawn uniformly from its parameter space (i.e., the Haar distribution, see Rubio-Ramírez et al., 2010).

We consider three scenarios. In the first scenario, labeled "homogeneous panel," shocks of the same type are identically distributed across all cross-sections without any cross-sectional correlations. In the second scenario, labeled "heterogeneous panel," shocks from different cross-sections have distinct distributions while remaining cross-sectionally

 $<sup>^{8}</sup>$ In Section S4, we present a comprehensive simulation study with stylized settings, where we also incorporate the dependence coefficient *C* introduced by Bakirov et al. (2006) and compare the performance of three alternative independence measures. As an alternative to minimizing the dependence statistic, we also explore the option of maximizing its *p*-value as proposed in Herwartz (2018). Notably, the simulation and empirical results discussed in this paper remain unchanged when switching to these alternative HL estimation settings.



**FIGURE 1** Simulation results for the identification of bivariate independent components. The left-hand side panel displays 18 data-generating distributions, encompassing uniform, Student's *t*, exponential, symmetric and asymmetric mixtures of Gaussian, and exponential distributions. The right-hand side panel depicts the distribution of the estimation error using boxplots, with medians marked by horizontal lines, covering various scenarios, estimation methods, and sample dimensions, with 1000 replications.

uncorrelated. In the third scenario, labeled "cross-sectionally correlated panel," we introduce cross-sectional correlations to the shocks generated from the first scenario as follows. Let the *N*-dimensional vectors  $\boldsymbol{\xi}_{t}^{(k)} = \left(\boldsymbol{\xi}_{1t}^{(k)}, \ldots, \boldsymbol{\xi}_{Nt}^{(k)}\right)'$  stack the structural shock  $k \in \{1, \ldots, K\}$  over all cross-section members at time *t*. Sets of *N*-dimensional structural shocks  $\left\{\boldsymbol{\xi}_{t}^{(k)}\right\}_{t=1}^{T}$  are drawn as

$$\boldsymbol{\xi}_{t}^{(k)} = Q^{1/2} \check{\boldsymbol{\xi}}_{t}^{(k)}, \, t = 1, \, \dots, \, T, \tag{10}$$

where  $Q^{1/2}$  is the symmetric matrix square root of the  $N \times N$  correlation matrix Q and  $\xi_t^{(k)}$  is the vector of structural shocks generated under the first scenario.<sup>9</sup> The typical [i, j]-th off-diagonal element of Q is  $\rho^{|i-j|}$ . We discuss results based on settings with a sizable correlation of neighbors using  $\rho = 0.6$ . In Section S2, we vary the cross-section correlations in different directions and investigate their effect on the performance of the proposed approach. Furthermore, we also consider additional scenarios that feature both cross-sectional heterogeneity and various degrees of cross-sectional correlations. Simulation results documented under these alternative scenarios lead to similar conclusions, as discussed below.

To assess the overall performance of the identification procedures in estimating the structural mixing matrix *Q*, we evaluate the Amari distance (see Matteson & Tsay, 2017)

<sup>&</sup>lt;sup>9</sup>The symmetric square root is given by  $Q^{1/2} = WV^{1/2}W'$ , where the eigenvectors of Q are the columns of W, and the diagonal matrix V has the eigenvalues of Q along its diagonal.

$$||Q, \hat{Q}||_{Amari} = \sum_{i=1}^{K} \left( \frac{\sum_{j=1}^{K} |r_{ij}|}{\max_{j} |r_{ij}|} - 1 \right) + \sum_{j=1}^{K} \left( \frac{\sum_{i=1}^{K} |r_{ij}|}{\max_{i} |r_{ij}|} - 1 \right),$$
(11)

with  $r_{ij} = (Q^{-1}\hat{Q})_{ij}$ . The Amari distance is invariant to sign flips and column permutations. Monte Carlo experiments cover two variants of the proposed HL estimator, which is either based on the statistic  $\mathcal{T}$  (HLdCov) or on  $\mathcal{B}$  (HLCvM). We also compare these variants with GMM estimation based on higher-order moment conditions (Lanne & Luoto, 2021) and the PML method (Gouriéroux et al., 2017), using a super-Gaussian (Student's t(5), PML(+)), and a sub-Gaussian (Gaussian mixture, PML(-)) pseudo density. For the purpose of GMM estimation, we impose the following (asymmetric) third- and fourth-order moments conditions

$$E\left[\left(\xi_{\tau}^{(k)}\right)^{2}\xi_{\tau}^{(k')}\right] = 0 \text{ and } E\left[\left(\xi_{\tau}^{(k)}\right)^{3}\xi_{\tau}^{(k')}\right] = 0 \text{ for all } k \neq k' \text{ and } k, k' \in \{1, \dots, K\}.$$
(12)

In each experiment, we first apply the alternative estimation methods independently to each panel member, compute Amari distances and document the average across all cross-sections. Subsequently, we employ these alternative estimation methods on the pooled sample (8) and evaluate the estimation error of the estimated common rotation matrix.

Simulation results as displayed in Figure 1 show that both GMM and HL estimation methods exhibit notable robustness against distributional heterogeneity of the independent shocks. However, the semi-parametric PML method, which relies on a fixed pseudo-density, carries the risk of misspecification and inconsistent estimation. Furthermore, when applied to pooled samples rather than pursuing cross-section-specific estimation, both GMM and HL estimation demonstrate a pronounced performance advantage. Importantly, this performance enhancement through pooling remains sizable even in the presence of cross-sectional heterogeneity and correlations, albeit with slight increases of estimation uncertainty. In contrast, PML estimation with fixed pseudo-densities does not benefit from exploiting pooled samples. Among the alternative measures of independence, HL estimation based on dCov statistics exhibits superior performance in smaller panels, while the use of CvM statistics can substantially benefit from an increase in sample information in either the time or cross-sectional dimension.

In summary, HL estimation based on the dCov statistic shows the most favorable finite-sample performance in terms of median estimation errors. This finding is particularly striking in panels of moderate size (N = 24, T = 120, 240). Considering its robustness against cross-sectional correlation and distributional heterogeneity, we deem this approach highly suitable for the proposed statistical identification in panel SVAR models.

#### 3.2 | Assessing monetary neutrality under a common shock

The data-generating-process (DGP) employed in the second experiment is a trivariate DSGE model comprising the output gap ( $x_t$ ), inflation ( $\pi_t$ ) and the nominal interest rate ( $r_t$ ) (see, e.g., Herwartz et al., 2022). The log-linearized structural model reads as follows:

$$x_{it} = \gamma_x E_t x_{it+1} + (1 - \gamma_x) x_{it-1} - \delta_{i,x} (r_{it} - E_t \pi_{it+1}) + \omega_{it}^{(x)}$$
(13)

$$\pi_{it} = (1 + \alpha\beta)^{-1}\beta E_t \pi_{it+1} + (1 + \alpha\beta)^{-1} \alpha \pi_{it-1} + \gamma_\pi x_{it} + \omega_{it}^{(\pi)}$$
(14)

$$r_{it} = \tau_r r_{it-1} + (1 - \tau_r)(\tau_\pi \pi_{it} + \tau_x x_{it}) + \omega_{it}^{(r)}$$
(15)

$$\omega_{it}^{(\bullet)} = \rho_{\bullet}\omega_{it-1}^{(\bullet)} + \xi_{it}^{(\bullet)}, \ \bullet \in \{x, \pi, r\}, \ t = 1, \ \dots, T, \ i = 1, \ \dots, N.$$
(16)

Equations (13), (14), and (15) represent an IS curve, a New Keynesian Phillips curve, and a policy reaction function given by the Taylor rule, respectively. All structural innovations in (16) are assumed to follow mutually independent autoregressive processes of order one with coefficients  $\rho_x$ ,  $\rho_\pi$ , and  $\rho_r$  for demand, supply, and MP shocks, respectively. Under the condition of equilibrium determinacy, the data-generating DSGE model implies a VAR(2) representation of  $y_{it} = (x_{it}, \pi_{it}, r_{it})'$  (see, e.g., Ravenna, 2007).

The DSGE model is calibrated in a common setting with parameter values  $\beta = 0.99$ ,  $\gamma_{\pi} = 0.05$ ,  $\tau_{\pi} = 1.8$ ,  $\tau_r = 0.6$  and  $\rho_x = \rho_r = \alpha = \gamma_x = \tau_x = \rho_{\pi} = 0.5$ . In each experiment, the parameter  $\delta_{i,x}$ , which governs the impact of the ex-ante real interest rate on the output gap, is drawn from a uniform distribution on the interval [0.05; 0.15]. Allowing  $\delta_{i,x}$  to vary across panel members is compelling for at least two reasons. On the one hand, such a setting is economically reasonable

			Freq. $\hat{d}_{13}^{MG} < 0$		Avg. $ \hat{d}_{13}^{MG} - Ed_{13} $		Avg. $  EQ, \hat{Q}_i  _{Amari}$	
	N	Τ	unpooled	pooled	unpooled	pooled	unpooled	pooled
Idiosyncratic MP shock	6	120	0.737	0.863	0.509	0.294	0.425	0.213
	6	240	0.838	0.960	0.436	0.183	0.339	0.125
	12	120	0.807	0.939	0.513	0.223	0.425	0.138
	12	240	0.895	0.998	0.431	0.112	0.337	0.083
	24	60	0.760	0.897	0.575	0.269	0.496	0.177
	24	120	0.875	0.989	0.521	0.130	0.426	0.088
	24	240	0.955	0.994	0.434	0.086	0.338	0.054
Common MP shock	6	120	0.722	0.807	0.483	0.404	0.465	0.269
	6	240	0.835	0.816	0.419	0.449	0.399	0.247
	12	120	0.800	0.958	0.486	0.214	0.443	0.137
	12	240	0.915	0.956	0.399	0.222	0.354	0.098
	24	60	0.752	0.962	0.559	0.216	0.498	0.144
	24	120	0.859	0.984	0.487	0.144	0.422	0.078
	24	240	0.969	0.976	0.390	0.140	0.332	0.055

TABLE 1 Simulation results for the DSGE model.

*Note*: From left to right: Average frequencies of detecting non-neutrality of MP, average absolute errors for the impact effect of MP on output, and average overall accuracy of the estimated rotation matrix  $\hat{Q}$  measured by the Amari distance. Model comparisons involve results from cross-section-specific estimation of rotation matrices ("unpooled") versus results obtained after pooling ("pooled"). The upper panel shows results for the model under fully idiosyncratic shocks. The lower panel shows results for the case of a common MP shock present in all cross-section members.

and realistic, as members of a monetary union might show stronger or weaker real effects of monetary policies.<sup>10</sup> On the other hand, since such an economically meaningful setting yet violates the assumption of the existence of a common rotation matrix Q, it is interesting to ascertain whether and in how far a cross-sectional pooling can still be beneficial for structural identifications. Given the favorable performance of HL estimation based on the dCov statistic, the second simulation experiment focuses on this statistical identification method.

To address the performance of panel SVAR estimation under fully idiosyncratic shocks on the one hand and in presence of cross-sectionally "identical" shocks on the other hand, we consider two alternative settings. The idiosyncratic shocks  $\{\xi_t^{(\bullet)}\}_{t=1}^T$  comprise independent standardized Student's *t* distributed random variables with degrees of freedom uniformly drawn from the interval [5; 8]. To establish that a particular shock is common to all cross-section members, we draw data for a system featuring a monetary policy shock that is shared by all cross-sectional entities (i.e.,  $\xi_{1t}^{(r)} = \ldots = \xi_{Nt}^{(r)}, \forall t$ ). After their generation, 100 pre-sample observations are discarded to immunize simulation outcomes against the initialization. Simulation experiments are performed 1000 times (M = 1000).

Since monetary policies in all panel sections are not neutral given that  $\delta_{i,x} > 0$ ,  $\forall i \in \{1, \dots, N\}$ , we report the frequencies of obtaining  $d_{13} < 0$  in an independence-based identification alternatively based on unpooled and pooled samples for various N, T combinations, that is, N = 6, T = 120,240; N = 12, T = 120,240; N = 24, T = 60,120,240. Furthermore, we document the average distance between  $\hat{d}_{m,13}^{MG}$  and its expected value given by the DGP, where  $\hat{d}_{m,13}^{MG}$  denotes the MG estimate of the structural impact multiplier of interest in experiment m. In specific, we compute average outcomes  $|\hat{d}_{13}^{MG} - Ed_{13}| := M^{-1} \sum_{m=1}^{M} |\hat{d}_{m,13}^{MG} - Ed_{13}|$ , where  $Ed_{13}$  is determined by Monte Carlo integration with 30,000 draws. In addition, we evaluate estimates for Q by means of the Amari distance defined in (11). In specific, let  $\hat{Q}_{m,i}$  denote the estimated rotation matrix for panel member i in experiment m, we document the average Amari distance

avg.
$$||EQ, \hat{Q}||_{Amari} = M^{-1}N^{-1}\sum_{m=1}^{M}\sum_{i=1}^{N}||EQ, \hat{Q}_{m,i}||_{Amari}$$

where the expectation *EQ* is determined by Monte Carlo integration. Notice that for identification based upon pooled samples,  $\hat{Q}_{m,1} = \ldots = \hat{Q}_{m,N}$  for all *m*.

As reported in Table 1, pooling panel time series data leads to more frequent estimates of non-neutral (i.e., negative) MP effects. In case T = 240, when the data are sufficiently informative for a fairly accurate LS estimation of the reduced

<sup>&</sup>lt;sup>10</sup>The impact multiplier of a contractionary MP shock for the output gap (i.e.,  $d_{i,13}$ ) is a monotone decreasing function of the DSGE parameter  $\delta_{i,x}$ . The value for  $d_{i,13}$  implied by a minimum (maximum) calibration of  $\delta_{i,x}$  is -0.24 (-0.55).

form, the frequencies of detecting the structural impact multiplier of interest with correct sign are throughout larger than 96% for the proposed panel SVAR estimator. By contrast, the corresponding frequencies that result from country-specific structural analyses in these scenarios are between 80% and 95%. Much like the qualitative assessment (sign), the proposed method also produces MG estimates with considerably better accuracy in a quantitative sense. The advantage of combining both data dimensions materializes when the panel dimension extends from N = 6 to N = 24 for a given time dimension. While both the average absolute bias of MG estimates  $d_{13}^{MG}$  and the estimation error of the matrix Q are reduced by more than one half for pooled samples (e.g., for T = 240 from 0.18 to 0.08 and from 0.12 to 0.05), results from country-level identifications remain largely unaffected (around 0.43 and 0.33). Unsurprisingly, the precise effect estimation for the common shock appears relatively challenging, especially when the available sample information is scarce. For instance, with data dimensions N = 6,12; T = 120, the pooling step offers only a mild improvement for the assessment of the effect of the common MP shock on economic activities. Nevertheless, the estimation of the complete rotation matrix Q considerably benefits from pooling in all scenarios considered, even in the presence of a common shock.

#### 4 | MONETARY POLICY TRANSMISSION IN THE EURO AREA

The process of monetary integration within the European Union, dating back to the late 1970s, reached a milestone with the introduction of the common currency on January 1, 1999. Academics and policymakers have shown substantial interest in the challenges faced by a single authority, namely, the ECB, conducting monetary policy within a heterogeneous environment. Notably, crucial market segments, such as labor and housing markets, are subject to marked institutional heterogeneity, and fiscal authorities retain the capacity to pursue country-specific expenditure plans and debt policies (e.g., Peersman, 2004; Georgiadis, 2015). However, studies explicitly focusing on post-1999 data are relatively limited. For instance, Neuenkirch and Nöckel (2018) investigate the manifestations of the "risk-taking channel" in the banking systems of 10 member countries of the monetary union by employing both recursive schemes and sign restrictions for identification. Another notable contribution is the dynamic factor model approach proposed by Corsetti et al. (2021), uncovering country-specific responses to MP shocks for a wide range of macroeconomic variables, with MP shocks being partially identified using high-frequency instruments.

The empirical analysis in this paper focuses on a dataset comprising 14 EA economies and covers the period from 2001Q1 to 2019Q4. We employ a set of VAR models consisting of four endogenous variables with additional exogenous variables (VARX). This set up is motivated by (i) the robustness of the three-variable MP model similar to the one employed in Section 3.2 (see, e.g., Plagborg-Müller & Wolf, 2021) and (ii) the role of financial conditions in assessing real effects of monetary policy (Caldara & Herbst, 2019). The suggested approach to panel SVAR identification is designed to unravel (i) country-specific responses of core macroeconomic variables (real GDP, inflation) to EA-wide shocks originating in MP and financial conditions, (ii) the interaction between the ECB and largely integrated financial markets, and (iii) a potential break in the MP transmission when the ECB switched from conventional short-rate adjustments to unconventional measures such as forward guidance and large-scale asset purchases.

In the following, we first explicitly outline the specific models employed at the country level and describe the estimation procedure. Second, we complement the analysis with a structural MP model for the entire EA. Third, we discuss panel SVAR results both at the monetary union level and for individual member countries. Fourth, we address potential changes in the MP transmission profile with the advent of unconventional policies.

To account for both estimation and identification uncertainty, we adopt bootstrap methods, which have been widely adopted in the existing literature. In particular, we employ variants of the wild bootstrap that are specifically tailored to preserve cross-sectional correlation patterns. The procedure is explained and further examined in Section S3.4.<sup>11</sup>

#### 4.1 | Panel SVARX specifications

Our analysis covers 10 EA member states that adopted the Euro in 1999 (Austria, Belgium, Finland, France, Germany, Italy, Luxembourg, the Netherlands, Portugal, and Spain), along with four other countries meeting Euro convergence cri-

<sup>&</sup>lt;sup>11</sup>A formal statistical analysis of bootstrap inference in panel SVARs is beyond the scope of this study. For a rigorous proof of asymptotic validity of a related bootstrap procedure in single SVAR models, the reader may consult Brüggemann et al. (2016).

teria later (Greece, Slovenia, Cyprus, and Malta). Countries joining the monetary union after the financial crisis (Slovakia in 2009, Estonia in 2011, Latvia in 2014, and Lithuania in 2015) are not included in the panel.<sup>12</sup>

We estimate 14 cross-section-specific VARXs models, each with distinct lag orders  $P_i$ , including an intercept, a linear, and quadratic deterministic trends:

$$y_{it} = \sum_{m=0}^{2} v_{im} t^m + B_i x_t + \sum_{p=1}^{P_i} A_{ip} y_{it-p} + u_{it},$$
(17)

where  $v_{im} \in \mathbb{R}^4$  for m = 0, 1, 2, and  $B_i$  and  $A_{ip} \in \mathbb{R}^{4 \times 4}$  for  $p = 1, \dots, P_i$ . The vector-valued variables  $y_{it}$  and  $x_t$  comprise both country-specific information and observations that are common to all cross section members or observed at a global level, that is,  $y_{it} = \left(y_{it}^{(1)'}, y_t^{(2)'}\right)'$ ,  $x_{it} = \left(x_{it}^{(1)'}, x_{it}^{(2)'}, x_t^{(3)'}\right)'$ . The first set of variables includes country-specific real activity and price measures, that is,  $y_{it}^{(1)} = (\Delta z_{it}, \pi_{it})'$ , where  $z_{it}$  and  $\pi_{it}$  denote the (log) real GDP and the annualized inflation of the (log) GDP deflator in country i and time t, respectively. Since the ECB is the only monetary authority aiming to ensure the price stability and the stability of (integrated) financial markets for the entire EA,  $y_t^{(2)} = (r_t, b_s_t)'$  comprises the EA-wide short-term interest rate and option-adjusted bond spreads, as indicators for the general monetary and financial conditions, respectively. Noticing that short-term rates approached the zero lower bound during the course of the financial and sovereign debt crisis, we employ shadow rates of Wu and Xia (2016) to capture MP signals for the periods following 2004Q4. To approximate EA financial conditions, we include option-adjusted spreads of high-yield bonds issued on EA bond markets.<sup>13</sup> Accounting for spillover effects, lag-exogenous variables  $x_{it}^{(1)} = \left(\Delta z_{-i,t-1}^{EA}, \pi_{-i,t-1}^{EA}\right)'$  comprise the first difference of log real GDP and the weighted inflation in the remaining countries, that is,  $z_{-i,t}^{EA} = \ln \sum_{j \neq i} e^{z_{j,t}}$  and  $\pi_{-i,t}^{EA} = e^{z_{j,t}}$  $\sum_{i\neq i} (\pi_{j,t} e^{z_{j,t}} / \sum_{i} e^{z_{j,t}})$ . Furthermore, we include trade volume (imports + exports) and government spending, both as a percentage of GDP, that is,  $x_{it}^{(2)} = (trade_{it}, ge_{it})'$  to control for openness and fiscal measures. Finally, we control for changes in global demand, inflation, and policy signals from the US central bank by including the inflation of a world commodity price index joint with the effective federal funds rate, that is,  $x_t^{(3)} = (\pi_t^W, r_t^{US})'$ . For graphical displays of the analyzed time series and data sources, see Section S3.1.

To determine the VARX orders  $P_i$ , we try to keep the reduced-form specification parsimonious and use the Schwarz information criterion (BIC) and a series of diagnostic tests to guide model selection. For a detailed discussion of model selection and diagnostic results (including tests on remaining serial correlation and fundamentalness), we refer the reader to Section S3.2. After the first-step LS estimation of country-specific VARs and the extraction of reduced form residuals  $\hat{u}_{it}$ , standardized and orthogonalized residuals are pooled as described in (8), and a common orthogonal rotation matrix is estimated using the dCov statistic.<sup>14</sup> Section S3.7 documents the HL-estimate of the common rotation matrix, along with bootstrap statistics.

In Section S3.3, we test the identifying assumption of mutual independence and its implications at the level of individual cross-sections, finding no evidence against the independence assumption. Further diagnostic results documented in Section S3.3 are largely supportive for the non-Gaussianity and the homogeneity of cross-sectional distributions of identified shocks.

#### 4.2 | One money, one market: an EA-wide model

When discussing the results obtained from the large-scale panel SVARX model, we compare structural outcomes with results from a well-understood aggregated EA-wide model:

$$y_{EA,t} = \sum_{m=0}^{2} v_{EA,m} t^m + B x_t^{(3)} + \sum_{p=1}^{P_{EA}} A_p y_{EA,t-p} + u_{EA,t},$$
(18)

<sup>&</sup>lt;sup>12</sup>Ireland is also excluded, since foreign direct investment plays an important role for its economy and aggregates reported in the national accounts may not precisely match the situation of real domestic activities.

<sup>&</sup>lt;sup>13</sup>High-yield bonds offer informative signals about changes of external financing costs and have been shown to exert significant explanatory power for general financial conditions and the business cycle. Structural estimates documented in this work remain largely robust when alternative financial indicators, such as changes in loans to the private sector, are employed.

<sup>&</sup>lt;sup>14</sup>Adopting an alternative independence measure—such as the Cramér-von-Mises distance—yield similar structural outcomes.

where  $y_{EA,t} = \left(y_{EA,t}^{(1)'}, y_t^{(2)'}\right)'$  with  $y_{EA,t}^{(1)} = (\Delta z_{EA,t}, \pi_{EA,t})'$  collects the real GDP growth and inflation for the EA at the aggregate level and  $y_t^{(2)} = (r_t, bs_t)'$  containing the MP and financial indicators as before. The lag order  $P_{EA} = 2$  minimizes the BIC and yields estimated residuals  $u_{EA,t}$  free of any serial correlation. Similar to the panel models, the EA-wide model is also identified by means of HL estimation based on the dCov statistic. The estimated structural impact multiplier reads as

$$\hat{D}_{EA} = \begin{bmatrix} 0.087 & -0.285 & -0.131 & -0.148\\ \scriptscriptstyle (0.153; 0.794) & (-0.182; -2.46) & (-0.039; -1.074) & (-0.053; -1.879)\\ 0.453 & 0.317 & -0.052 & 0.041\\ \scriptscriptstyle (0.216; 2.115) & (0.331; 2.412) & (-0.016; -0.404) & (-0.018; 0.315)\\ 0.123 & -0.062 & 0.276 & -0.035\\ \scriptscriptstyle (0.051; 1.312) & (0.015; -0.706) & (0.233; 4.731) & (0.018; -0.600)\\ 0.000 & -0.397 & 0.159 & 1.025\\ \scriptstyle (-0.028; -0.001) & (-0.082; -1.611) & (0.031; 0.857) & (0.858; 6.083) \end{bmatrix},$$

where the values in parentheses (a; b) denote the bootstrap means (a) and t-ratios (b). The sign patterns of columns of  $\hat{D}_{EA}$ allow for an economic labeling of the shocks. Specifically, the shock identified in the first column, which moves output and prices in the same direction, can be classified as a demand shock. Conversely, the shock in the second column, which moves output and prices in opposite directions, qualifies as a supply shock. However, the main focus of this research is primarily on analyzing the transmission of MP and financial shocks. Of particular interest are the shocks in the third column, which have the strongest impact on interest rates, and the shocks in the fourth column, which have the strongest impact on bond spreads. While both shocks exhibit opposite effects on prices and short-term rates, aligning with the characteristic response of MP shocks, the magnitude of the effects on short-term rates allows us to identify the shock in the third column of  $\hat{D}_{EA}$  as a contractionary MP shock. In labeling the shock in the fourth column of  $\hat{D}_{EA}$ , it is important to consider its impact on output and interest rates. The tightening of financial conditions leads to a significant reduction in economic activity. In response to this shock, short rates show a relatively mild downward impact, indicating a potentially accommodating MP conduct. The structural impulse response functions (IRFs) depicted in Figure 2 underpin the adverse effects of both MP and financial shocks on economic activity. Additionally, financial conditions experience a temporary deterioration following a MP shock. Therefore, financial conditions can be seen as a potential channel through which adverse effects of MP on economic activity occur. Neglecting this channel could result in misidentification of the MP shock, as emphasized by recent findings in the context of the US economy by Caldara and Herbst (2019).

#### 4.3 | One money, many markets: evidence from panel SVARs

## 4.3.1 | Weighted mean group IRFs

To examine the structural implications derived from the panel model, we begin by investigating whether the findings obtained from the EA-wide model align with the outcomes observed in the panel model at the MG level. The estimated structural impact multipliers, along with the examination of the resulting IRFs, enable us to assign economic interpretations to the identified shocks in a single SVAR model comprising EA-aggregates. Specifically, we find that the shocks with the size of one standard deviation, which cause the most significant and pronounced instantaneous reactions in the short rate and bond spreads, are identified as MP and financial shocks, respectively. Taking this into account, the MG estimates for the structural impact multiplier obtained from the panel SVAR identification support the interpretation of the third and fourth shocks as MP and financial shocks, respectively. Implied IRFs provide additional evidence in support of this interpretation. Figure 2 presents the (weighted) MG estimates of structural IRFs (along with 16% and 84% bootstrap coverage bands) for normalized MP and financial condition shocks. The MG estimates are computed by assigning weights to the cross-sectional IRFs based on the average share of their respective real GDP over the sample period. The MP and financial conditions shocks are normalized to have +25 bps instantaneous effects on the short rate and bond spreads, respectively. As it emerges, the identified panel SVAR models and the EA-wide model exhibit a remarkably high degree of agreement regarding the core transmission patterns for both shocks.

MP shocks invoke a gradual off-tapering in the short rate, while their effects on inflation are temporary and mild at the MG level, which confirms insights from previous studies (e.g., Slacalek et al., 2020). Unlike inflation, the responses of output are persistent and significant. Following an unexpected tightening of MP, the real GDP experiences a decline of approximately 0.2% and 0.25% at the MG level after 2 and 5 years, respectively. Additionally, external financing costs increase, and financial conditions deteriorate significantly as a result of the monetary contraction. The response of





**FIGURE 2** Weighted mean group responses to MP and financial shocks in panel SVARX (green dashed) models and the area-wide model (blue solid). Both shocks are normalized to have an impact effect of 25 bps on the respective variables. Shaded areas indicate a coverage band composed from 16% and 84% quantiles of the bootstrap distribution of the estimates based on 1000 replications.

financial conditions exhibits a hump-shaped profile, with bond spreads climbing towards 30 bps and remaining above 10 bps for 2.5 years after the shock. The response profile of credit spreads shows notable similarities with the findings of Caldara and Herbst (2019) for the United States, despite differences in model composition and variables used.<sup>15</sup> Furthermore, our results align with the role of the "risk-taking channel" within the EA as explored by Neuenkirch and Nöckel (2018). The observed increase (decrease) in the required reward for holding risky assets in response to an unexpected monetary tightening (easing) amplifies the impact of MP.

As shown in the right panel of Figure 2, an exogenous tightening of financing costs leads to a significant contraction in output, with real GDP shrinking by approximately 0.05% in just one quarter following the shock. In response to this countercyclical effect, the central bank adopts accommodative policies by reducing the short-term interest rate by around 3 bps after one quarter. However, as bond spreads return to their initial levels within 2 years, the effects on the short rate diminish and become insignificant in the medium to long terms.

# 4.3.2 | Country-specific sensitivity to monetary policy and financial condition shocks

Having established that the MG estimates derived from the panel SVAR models largely replicate the economically meaningful outcomes obtained from the EA-wide model, we proceed to exploit the specific advantages offered by a panel data framework. The panel model enables the simultaneous modeling of multiple markets, allowing us to explore the hetero-

<sup>&</sup>lt;sup>15</sup>Besides a slightly different and larger set of variables, in particular, the Bayesian approach in Caldara and Herbst (2019) builds upon high-frequency proxies and exclusion restrictions (i.e., a block Cholesky factor) to identify MP and financial shocks, respectively. Quantitative differences between their results for the United States and ours for the EA can be partly addressed to the fact that European bond markets are less liquid in comparison with US markets and that we employ spreads of below-investment-grade bonds.



**FIGURE 3** Response of the real GDP in the EA (black solid) and its member states (colored dashed) to a MP (upper panel) and financial shock (lower) identified by means of Cholesky scheme (left panel) and the Hodges-Lehmann estimation by minimizing dependence using distance covariance (right). The MP (financial) shock is normalized to have an impact effect of 25 bps on the short rate (bond spreads).

geneous effects of MP shocks across different cross-sections, as also examined by Corsetti et al. (2021). Furthermore, we conduct a similar analysis concerning financial shocks.

We begin by comparing country-specific structural outcomes from the panel SVAR model with estimates obtained from a recursive scheme, which is conventionally used to identify MP and financial shocks based on the assumption that slow-moving variables (such as output and inflation) do not respond immediately to surprise information in monetary policy and financial markets. Results are illustrated in Figure 3. At the weighted MG level, both approaches yield reasonable responses of the output to contractionary MP shocks and unexpected deteriorations in financial conditions. These shocks generally lead to declines in economic activity. However, for certain member states (such as Malta, Slovenia, and Greece), the recursive scheme produces puzzling positive output responses following an unexpected tightening in MP or financial conditions. These counter-intuitive patterns are particularly pronounced for responses to financial shocks. In contrast, the panel SVAR approach generates negative output responses to adverse MP or financial shocks for all panel members and across various horizons. Interestingly, the patterns of country-specific output responses to MP shocks closely resemble the results in Corsetti et al. (2021) (see fig. 5 in their paper), which reflect considerable heterogeneity across important market segments within the EA, such as labor markets, housing, and mortgage markets. While a detailed analysis focusing on the structural origins of country-specific results is beyond the scope of this study, the observed heterogeneous response profiles provide valuable insights for future research in these areas. Additionally, in Section S3.5, we present the estimated country-specific responses of inflation. In line with the modest and inconclusive pattern observed in the response profile at the MG level, the country-specific responses of inflation demonstrate substantial heterogeneity. This finding also aligns with the evidence presented in Corsetti et al. (2021), who find that the price responses to an unexpected monetary contraction are positive for half of the countries and negative for the remaining half.

To further illustrate the benefits of combining both data dimensions through cross-sectional pooling, we also conduct statistical identifications by imposing independent shocks at the individual cross-sectional level, as typically done in the statistical identification of single SVAR models. Specifically, we employ alternative estimators investigated in Section 3, including the HL estimator based on the dCov statistic, GMM with moment conditions in (12), and PML based on a

Student's *t* pseudo density with 5 degrees of freedom. The estimated country-specific real effects of MP and financial shocks obtained from these approaches are presented in Section S3.6. Notably, with limited sample information of approximately 78 observations at the cross-sectional level, the statistical identifications produce implausible and outlying output responses. This issue is particularly severe for results obtained from the GMM and PML approaches. These findings are consistent with the simulation-based evidence documented in Section 3.1.

Finally, considering the inclusion of EA-wide information in the VAR models, it is interesting to examine whether the panel SVAR effectively captures "common" MP and financial shocks. The analysis reveals a striking similarity in the informational content of both shocks extracted from the panel SVAR models, The correlation coefficients between the shocks range from 0.72 (for Finland and Portugal) to 0.95 (for France and Spain) for MP shocks and from 0.61 (for Finland and Italy) to 0.92 (for Spain and Portugal) for financial shocks.

#### 4.3.3 | Structural change of transmission mechanisms

Up until now, our findings from both the EA-wide and panel SVAR models have been based on the assumption that MP transmission within the EA has remained stable over time. However, with central banks facing policy rates nearing the zero lower bound, they have implemented unconventional policy measures such as forward guidance and asset purchasing programs. It is still unclear whether these changes in policy conduct have led to modifications in the transmission mechanism of shocks (see, e.g., Swanson, 2021). For instance, in July 2013, the ECB added forward guidance to its toolbox for the first time by communicating future MP intentions. In mid-2014, the ECB adopted the negative interest rate policy in order to contain the unprecedented disinflationary risks.

To investigate possible changes in the transmission of monetary and financial shocks for the periods of conventional and unconventional policies, we conduct separate HL estimations and search for the optimum rotation that minimizes



**FIGURE 4** Weighted MG responses to monetary policy  $(\xi_{3t})$  and financial shocks  $(\xi_{4t})$  in panel SVARX models as identified from subsamples covering pooled standardized residuals from the pre- and post mid-2013. For further notes and full sample estimates, see Figure 2.

the dependence among pooled orthogonalized residuals that belong to time instances up to and after 2013Q2, which has also been considered by Cieslak and Schrimpf (2019).<sup>16</sup> More explicitly, in the notation of Section 2.2 (in particular, see Equation (8)), the reduced-form systems are estimated using full sample information, from which two pooled subsamples of orthogonalized residuals are retrieved, namely,

$$\mathcal{A}_{\theta}^{(N, pre)} = \{\{\xi_{\theta, it}\}_{t \in pre}\}_{i=1}^{N} \text{ and } \mathcal{A}_{\theta}^{(N, post)} = \{\{\xi_{\theta, it}\}_{t \in post}\}_{i=1}^{N}.$$
(19)

From these subsamples, the detection of independent components yields two alternative estimates of rotation matrices, that is,  $\hat{Q}^{(pre)}$  and  $\hat{Q}^{(post)}$ , which are subsequently used to derive structural parameter matrices  $\hat{D}_i^{(pre)}$ ,  $\hat{D}_i^{(post)}$  as formalized in equation (9). Since we do not find evidence against the stability hypothesis based on a Chow test, we abstain from estimating the reduced form VARs for each subsample period.

Impulse responses in Figure 4 indicate whether and to what degree the transmission of MP and financial shocks changed during the period of unconventional policies. Interestingly, the shape, locations, and significance of these IRFs closely resemble the results obtained for the full sample as depicted in Figure 2, which is consistent with the findings of Swanson (2021) for the United States. Formal Wald-tests also support these observations, as we do not detect changes in the structural impact multiplier at the weighted MG level with common significance. However, there are a few note-worthy observations to be made. In comparison to the results from the first subsample, there appears to be a stronger interaction between monetary and financial conditions in more recent years. Specifically, a contractionary policy shock invokes a more immediate response in bond spreads and leads to a faster and more pronounced deterioration in financial conditions. Conversely, a tightening of financial conditions coincides with a stronger accommodative response from MP, both in the short-term and over longer horizons.

#### **5 | CONCLUSIONS**

This paper introduces a novel method for identifying panel SVAR models by imposing statistical independence on the structural innovations at the pooled level. The proposed approach identifies a common rotation of orthogonalized cross-section-specific reduced-form model residuals. Following the principles of Hodges-Lehmann estimation, a unique structural model is derived by minimizing a selected independence measure, such as the distance covariance introduced by Székely et al. (2007) and suggested by Matteson and Tsay (2017) for ICA. Monte Carlo exercises showcase the performance benefits achieved by combining both data dimensions while explicitly accounting for cross-sectional correlations and heterogeneity of distributional patterns.

Results derived from the panel SVARX model enable a robust labeling of monetary policy (MP) shocks and shocks to financial conditions in the Euro area. We document interactions between the short rate and bond spreads, as well as substantial cross-sectional heterogeneity in the real effects of MP. Notably, the estimated effects of MP shocks remained largely unchanged when the European Central Bank has resorted to unconventional policy tools. The identified heterogeneity in the real effects of MP in member states suggests a need for further exploration, similar to the approach taken by Corsetti et al. (2021). Expanding upon their benchmark study and considering the interaction between MP and financial conditions highlighted in this work, a crucial avenue for future research could involve a nuanced understanding of housing markets and the financial balance sheets of households in the transmission of MP and financial shocks. Another intriguing macroeconomic application includes analyzing the impact of currency appreciations on country risks in economies with holdings of US dollar-denominated assets (Bernoth & Herwartz, 2021; Goodhart & Hofmann, 2008). The panel SVAR approach may prove beneficial in enhancing structural estimations of such relationships under limited time series information, typically encountered in the study of emerging economies.

#### ACKNOWLEDGMENTS

We express our sincere gratitude to Co-editor Marco Del Negro and the six anonymous referees for their insightful suggestions and constructive feedback. We would also like to extend our appreciation to Christiane Baumeister, Kai Carstensen, Lennart Empting, Matthias Hartmann, Bernd Hayo, Sebastian Hienzsch, Helmut Lütkepohl, Matthias Neuenkirch,

<sup>16</sup>We have also examined an alternative break occurring in mid-2010. Conditioning on this break point leads to structural IRFs that are very similar to the results discussed here (see Section S3.8).

Christian Ochsner, Werner Roeger, Lasse Trienens, and Henning Weber for helpful comments. We gratefully acknowledge financial support by the Deutsche Forschungsgemeinschaft (HE 2188/8-2; 2188/17-1).

# OPEN RESEARCH BADGES

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This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at https://doi.org/10.15456/jae.2024044.1425287131.

#### DATA AVAILABILITY STATEMENT

The data that support the empirical findings of this study are openly available. The sources of individual time series are documented in Section S3.1 of the supplementary material.

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#### SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of the article.

**How to cite this article:** Herwartz, H., & Wang, S. (2024). Statistical identification in panel structural vector autoregressive models based on independence criteria. *Journal of Applied Econometrics*, *39*(4), 620–639. https://doi.org/10.1002/jae.3044

#### **APPENDIX A: PROOF OF THEOREM 1**

Lemma 1 (Darmois-Skitovich). For two scalar random variables  $L_1$  and  $L_2$  of the linear form

$$L_1 = \sum_{k=1}^{K} \alpha_k \xi_{\tau}^{(k)} \text{ and } L_2 = \sum_{k=1}^{K} \beta_k \xi_{\tau}^{(k)}, \tag{A1}$$

where  $\xi_{\tau}^{(k)}$  are independent scalar random variables for k = 1, ..., K, which are not necessarily identically distributed. If  $L_1$  and  $L_2$  are independent, all variables  $\xi_{\tau}^{(k)}$  whose coefficients satisfy  $\alpha_k \beta_k \neq 0$  are Gaussian.

The proof of Lemma A.1 relies on the application of Cramér's theorem (Cramér, 1936) and a extended version of the Marcinkiewicz's theorem. The latter states that if a characteristic function has the form  $\phi(s) = E \exp P(t)$ , where P(t) is a polynomial, then P(t) is at most a quadratic polynomial, and  $\phi(s)$  corresponds to the characteristic function of a normal law (see, e.g., Linnik, 1964). A detailed proof of Lemma A.1 can be found in standard statistical textbooks that address characterization problems, such as Section 3 of Kagan et al. (1973).

Now, let  $\xi_{\tau}$  represent the vector of true independent structural shocks, where at most one of  $\xi_{\tau}^{(k)}$  is Gaussian. Suppose that there exists another vector of independent components, denoted as  $\check{\xi}_{\tau} = \check{Q}\xi_{\tau}$  and  $\check{Q}$  is not equal to  $\Lambda \mathcal{P}$ . As the components in  $\check{\xi}_{\tau} = \left(\check{\xi}_{\tau}^{(1)}, \ldots, \check{\xi}_{\tau}^{(K)}\right)'$  are independent and  $\check{Q}$  differs from  $\Lambda \mathcal{P}$ ,  $\check{Q}$  will necessarily contain two non-zero elements in at least two distinct columns. Let us denote these columns as  $k_1$  and  $k_2$ , and without loss of generality, suppose that the non-zero elements are  $\check{q}_{m,k_1}$  and  $\check{q}_{n,k_2}$  with  $\check{q}_{i,j}$  being the [i, j]-th element in matrix  $\check{Q}$   $(k_1, k_2, m, n \in \{1, \ldots, K\}, k_1 \neq k_2, m \neq n)$ . Note that

$$\check{\xi}_{\tau}^{(m)} = \sum_{k=1}^{K} \check{q}_{m,k} \xi_{\tau}^{(k)} \text{ and } \check{\xi}_{\tau}^{(n)} = \sum_{k=1}^{K} \check{q}_{n,k} \xi_{\tau}^{(k)},$$
(A2)

where  $\xi_{\tau}^{(m)}$  and  $\xi_{\tau}^{(n)}$  are independent. Since  $\check{q}_{m,k_1}\check{q}_{n,k_1} \neq 0$  and  $\check{q}_{m,k_2}\check{q}_{n,k_2} \neq 0$ , according to Lemma A.1, the corresponding shocks  $\xi_{\tau}^{(k_1)}$  and  $\xi_{\tau}^{(k_2)}$  must be both Gaussian. This contradicts our identifying Assumption 1, which states that at most one of  $\xi_{\tau}^{(k)}$  is Gaussian. Therefore,  $\check{Q}$  must take the form  $\Lambda \mathcal{P}$ , which implies that elements in  $\check{\xi}_{\tau}$  are the same as those in  $\xi_{\tau}$  with a permutation and sign flips.