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Katja Heinisch, Fabio Scaramella, Christoph Schult

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Authors

Katja Heinisch
Corresponding author
Halle Institute for Economic Research (IWH) – Member of the Leibniz Association,
Department of Macroeconomics
E-mail: katja.heinisch@iwh-halle.de
Tel +49 345 7753 836

Fabio Scaramella
University of Bologna

Christoph Schult
Halle Institute for Economic Research (IWH) – Member of the Leibniz Association,
Department of Macroeconomics
E-mail: christoph.schult@iwh-halle.de
Tel +49 345 7753 806

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Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Address: Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany
Postal Address: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

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Assumption Errors and Forecast Accuracy: A Partial Linear Instrumental Variable and Double Machine Learning Approach*

Abstract

Accurate macroeconomic forecasts are essential for effective policy decisions, yet their precision depends on the accuracy of the underlying assumptions. This paper examines the extent to which assumption errors affect forecast accuracy, introducing the average squared assumption error (ASAE) as a valid instrument to address endogeneity. Using double/debiased machine learning (DML) techniques and partial linear instrumental variable (PLIV) models, we analyze GDP growth forecasts for Germany, conditioning on key exogenous variables such as oil price, exchange rate, and world trade. We find that traditional ordinary least squares (OLS) techniques systematically underestimate the influence of assumption errors, particularly with respect to world trade, while DML effectively mitigates endogeneity, reduces multicollinearity, and captures nonlinearities in the data. However, the effect of oil price assumption errors on GDP forecast errors remains ambiguous. These results underscore the importance of advanced econometric tools to improve the evaluation of macroeconomic forecasts.

Keywords: accuracy, external assumptions, forecasts, forecast errors, machine learning

JEL classification: C14, C53, E02, E37

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1 Motivation

The accuracy of macroeconomic forecasts—and their effectiveness in guiding policy—hinges on the reliability of their underlying assumptions. Persistent disagreement and heterogeneity among professional forecasters, as documented in the literature (e.g., Andrade *et al.*, 2016; Juodis and Kučinskas, 2023; Glas and Hartmann, 2022), add further complexity to forecast evaluation. These discrepancies vary over time, highlighting the importance of understanding the mechanisms driving forecast updates (revisions) and errors. A key factor influencing macroeconomic forecasts is the set of assumptions—or expectations—regarding central conditioning variables, such as realized values and expected future paths (Glas and Heinisch, 2023). For instance, evidence from the European Central Bank (ECB) highlights the significant influence of oil price on short-term inflation expectations in the euro area (Baumann *et al.*, 2021). Understanding the extent to which such expectations about these variables shape the forecast accuracy is thus crucial for both researchers and policymakers. However, despite their importance, assumptions are rarely documented in a consistent manner and have not been systematically analyzed in the existing literature (e.g., Keereman, 2003; Takagi and Kucur, 2006; Fioramanti *et al.*, 2016; Berge *et al.*, 2019; Engelke *et al.*, 2019; Heinisch *et al.*, 2024). This lack of transparency limits our ability to evaluate the relationship between assumption errors and forecast performance. In addition, model specification and estimation techniques significantly impact the accuracy of the forecast. Traditional methods often encounter methodological limitations, including endogeneity, multicollinearity, and high dimensionality. To address these challenges, recent studies propose machine learning-based econometric techniques, which offer flexible modeling structures and improved prediction accuracy. Chernozhukov *et al.* (2018) introduce double/debiased machine learning (DML) as a powerful tool for causal inference in high-dimensional settings. Using these algorithms to estimate nuisance parameters while preserving valid statistical inference, DML is particularly useful to address endogeneity in macroeconomic forecasting. Empirical applications of DML in real data contexts include studies by Shi *et al.* (2023), Wyrembek *et al.* (2024), Guo *et al.* (2024), and Kalanatha Bhatta (2023), covering energy and labor markets.

To our knowledge, this is the first study to apply the double machine learning–partial linear instrumental variable (DML-PLIV) framework in the context of macroeconomic forecasting. We utilize a novel dataset of forecasts and assumptions for Germany published by multiple forecast institutions. The dataset covers forecasts for GDP growth and key conditioning variables, including oil price, exchange rate, world trade. This enables us to assess the impact of assumption errors on forecast accuracy. Building on previous research by Heinisch *et al.* (2024) and Engelke *et al.* (2019), who identify a positive relationship between squared assumption errors (SAE) and squared forecast errors (SFEs) for German GDP growth, we extend their analysis by employing a semiparametric approach that accounts for endogeneity and nonlinearities. Although their findings provide valuable information, their reliance on Ordinary Least Squares (OLS) regression presents key limitations in addressing endogeneity and capturing complex, nonlinear relationships. Effective causal inference extends beyond the identification of the direction of relationships, requiring a precise quantification of their magnitude. To address these challenges, this paper applies partial linear instrumental variable (PLIV) regression models with DML methods (Chernozhukov *et al.*, 2018). This methodology enables a semiparametric analysis that overcomes the constraints of traditional OLS models through three key contributions:

First, the DML framework is particularly well suited for managing large, structured datasets where traditional parametric methods fail. PLIV-DML provides a reliable structure for shaping a complex set of confounding covariates. Forecast errors are influenced by numerous macroeconomic and institutional factors, which require a model capable of handling complex interactions. OLS-based methods often struggle to incorporate multiple fixed effects and time-varying influences. Heinisch *et al.* (2024), for instance, estimated over 330 parameters, primarily to capture fixed effects and interaction terms. In contrast, PLIV-DML efficiently selects and estimates relevant variables without overfitting. Similarly, our analysis incorporates a high-dimensional covariate structure to account for confounding factors, ensuring precise parameter estimates while mitigating endogeneity. Similarly to Schlaak *et al.* (2023), we use diagnostic tests to evaluate two-stage least squares (2SLS) regressions and assess the validity of potential instruments.

Second, PLIV-DML allows for more complex relationships between forecast errors and assumption errors. In particular, we hypothesize mutual dependencies between the squared forecast errors of GDP and the squared assumption errors of key variables such as oil price, exchange rate, and world trade. Unlike standard OLS, which imposes a strictly linear and unidirectional relationship, the PLIV-DML approach accounts for these interactions by incorporating instrumental variables to address potential endogeneity, thereby allowing for a more flexible and robust analysis of these interdependencies. This type of simultaneous influence aligns with evidence from Tunc *et al.* (2022), which highlights simultaneous influences between GDP and oil price in the German context. In addition, DML allows for controlling possible interconnections among the assumption errors.

Finally, the validity of empirical models hinges on two critical assumptions: (i) forecaster rationality and (ii) linearity of the data-generating process. The rationality assumption stipulates that forecasters utilize all available information efficiently when making predictions. However, Fritsche and Döpke (2005) provide evidence of non-rational behavior among Germany's six leading economic institutes, raising questions about the validity of this assumption. The linearity assumption, on the other hand, suggests that forecast errors can be adequately modeled as a linear function of assumption errors and unobserved components. We argue that the assumptions significantly influence model specification and the choice of analytical techniques. Using PLIV-DML, we explicitly test for potential nonlinearities and interaction effects, providing a more flexible model specification than previous OLS-based studies.

The paper is organized as follows. Section 2 provides an overview of the forecasts and their underlying assumptions. Section 3 details the regression framework and causal inference methodology, with the corresponding regression results presented in Section 4. Finally, Section 5 concludes the paper.

2 Forecasts and Forecast Errors

The dataset comprises forecasts of German annual GDP growth for both the current and the subsequent year, compiled from 12 national (in particular economic research institutes and Deutsche Bundesbank) and international forecasters (European Commission, IMF, OECD) (Table A1).[1] These institutions update their forecasts during the year—some at quarterly frequency while others revise their forecasts less frequently (Figure A1). Hence, for a particular target year, multiple forecasts are available from each institution. The longest forecast horizon in our dataset extends eight quarters ahead, capturing projections for the following year made in the first quarter of the current year.[2] Our evaluation period extends from 1992 to 2019, covering a total of 1,460 GDP forecasts — 758 for the current year and 702 for the subsequent year provided by 12 forecast institutions.

In addition to GDP forecasts, forecast institutions disclose key assumptions underpinning their projections that cover the external environment. While not specific to Germany, they are central to its economic outlook. These include the oil price, world trade growth rates, and the US dollar/Euro exchange rate. Despite their relevance, the documentation of these assumptions varies considerably between institutions and over time, particularly in terms of target definitions (e.g., annual averages versus end-of-year values). To address this heterogeneity issue, our empirical analysis incorporates institution-specific and time-specific fixed effects to account for heterogeneity in assumption targets. This adjustment ensures that discrepancies in reported values do not bias cross-institutional comparisons. Our dataset includes a substantial number of observations for assumptions: 1,159 for oil price, 1,123 for exchange rate, and 740 for world trade.[3] However, not all institutions systematically report all the assumptions, resulting in a final sample of less than 700 observations in models in which all three assumptions are included. This data constraint highlights the challenges of conducting a fully comprehensive cross-institutional analysis while ensuring empirical robustness. Additionally, the volatility of GDP forecasts and assumption values fluctuates over time, especially for oil price projections.

Forecast errors (FE) and assumption errors (AE) are calculated for each institution n as the difference between the predicted and realized values for GDP and the respective assumptions conducted at year t. They are measured for the target year $t+h$ with a forecast horizon $h \in [0, 1]$:

$$FE_{n,t+h|t} = \hat{y}_{n,t+h|t} - y_{t+h}, \tag{1}$$

$$AE_{n,t+h|t} = \hat{a}_{n,t+h|t} - a_{t+h}. \tag{2}$$

The resulting forecast errors exhibit great variance across different forecast horizons (Figure 1), indicating that institutions rely on different assumptions even when forecasting GDP for the

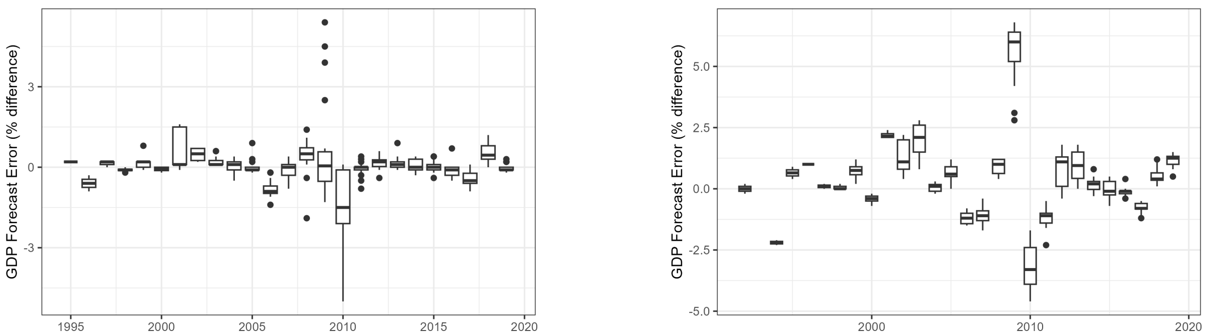
[1] See IWH Forecasting Dashboard: `https://halle-institute-for-economic-research.shinyapps.io/economic-forecast/`

[2] Further details on forecast horizons are available in the Appendix. Figure A1 illustrates the varying number of forecasts per year, which ranges from zero to eight updates. Certain institutions publish forecasts beyond an eight-quarter horizon.

[3] Detailed summary statistics are provided in Table A2 in the Appendix.

Figure 1: GDP Forecast Errors

(a) **Forecast horizon** $h = 0$ (b) **Forecast horizon** $h = 1$



Note: Range of forecast errors conducted in the current year ($h = 0$) or in the previous year ($h = 1$) for a particular target year.

same horizon. On average, forecasts tend to be too optimistic, except for the oil price (Table A2). The degree of heterogeneity in the forecast errors increases with the forecast horizon (Figure A2).

Suppose a forecaster aims to predict future macroeconomic outcome y_{t+h}, using a forecasting model based on a set of assumed exogenous assumptions a_{t+h} (e.g., world trade). The true data-generating process (DGP) is:

$$y_{t+h} = f(a_{t+h}, z_t) + \epsilon_{t+h} \tag{3}$$

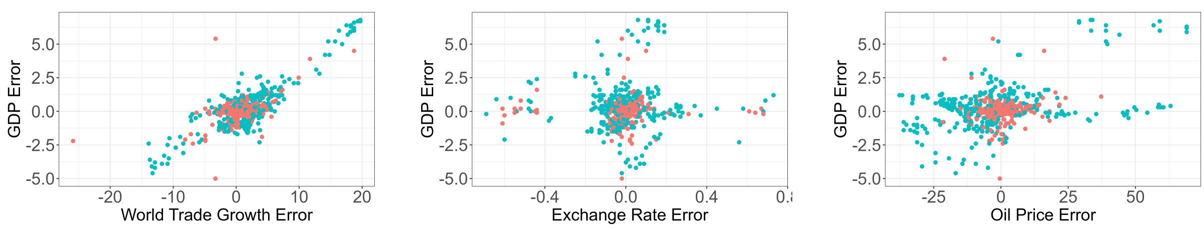
However, since a_{t+h} is not observable at year t, the forecaster uses an assumed value $\hat{a}_{n,t+h|t}$ to derive the forecast:

$$\hat{y}_{n,t+h|t} = f(\hat{a}_{n,t+h|t}, z_t) \tag{4}$$

Correlations across GDP forecast errors and assumption errors are generally positive in the case of world trade, but the picture is less clear for oil price and exchange rate (Figure 2).

Figure 2: Forecast Error Correlation

(a) **World Trade** (b) **Exchange Rate** (c) **Oil**



Note: Correlation between GDP forecast errors and different assumption errors for the current year (red) and next year (blue).

To assess forecast accuracy and the impact of assumption errors, we analyze the squared forecast error (SFE) (5) for GDP and squared assumption errors (SAE) (6) for each conditioning variable. While forecast and assumption errors preserve the sign of the mistake, the squared errors focus on the magnitude of errors. For a forecast made by institution n at year t for target year $t+h$, these are defined as

$$SFE_{n,t+h|t} = \left(\hat{y}_{n,t+h|t} - y_{t+h}\right)^2, \tag{5}$$

$$SAE_{n,t+h|t} = \left(\hat{a}_{n,t+h|t} - a_{t+h}\right)^2, \tag{6}$$

respectively. Hence, in a conceptual model centered on forecast accuracy, larger assumption errors (in absolute terms) lead to larger GDP forecast errors. A key issue is that assumption errors may be endogenous in forecast error regressions. Therefore, to investigate the persistence of assumption errors over time, we construct a lagged squared assumption error (LSAE), which reflect a one-year lag to the forecast target year and to the year at which the forecast has been made (7). To control for potential reverse causality between forecast and assumption errors, we compute the average squared assumption error (ASAE) across all institutions $i \in \{1, \dots N\}$, except the one analyzed ($i \neq n$), for the same forecast target year and horizon (8). In addition, to account for the persistence of assumption errors over time, we introduce LASAE (9), which applies a one-year delay.

$$LSAE_{n,t+h|t} = \left(\hat{a}_{n,t+h-1|t-1} - a_{t+h-1}\right)^2 = SAE_{n,t+h-1|t-1} \tag{7}$$

$$ASAE_{n,t+h|t} = \frac{1}{N-1}\sum_{i\neq n} SAE_{i,t+h|t} \tag{8}$$

$$LASAE_{n,t+h|t} = ASAE_{n,t+h-1|t-1} = \frac{1}{N-1}\sum_{i\neq n} SAE_{i,t+h-1|t-1} \tag{9}$$

These variables enhance the robustness of our instrumental variable approach in the 2SLS regressions and improve the predictive accuracy of the DML model by mitigating potential biases in assumption-based forecasts.

3 Regression Analysis and Causal Inference

3.1 Traditional Econometric Approaches

This section outlines the implementation of traditional econometric methods: Ordinary least squares (OLS) and two-stage least squares (2SLS) to analyze the impact of assumption errors on GDP forecast errors. Unlike modern machine learning approaches, these methods rely on different parametric assumptions and linear relationships. The OLS-based models, following

Heinisch *et al.* (2024), examine the relationship between each SAE (D) and the SFE of GDP (Y), controlling for additional covariates $\mathbf{X}$:[4]

$$Y = \beta_0 + \mathbf{D}\boldsymbol{\beta}_1 + \mathbf{X}\boldsymbol{\gamma} + \epsilon, \tag{10}$$

where β_0 is the intercept, $\boldsymbol{\beta}_1$ captures the effect of the squared assumption errors $\mathbf{D}$ on Y, $\boldsymbol{\gamma}$ represents the coefficients associated with the covariates X, and ϵ is the error term. Although OLS provides a simple estimation strategy, it assumes exogeneity of $\mathbf{D}$, ignores potential non-linearities, and does not account for mutual dependencies between Y and each D. We employ the 2SLS method to overcome the potential endogeneity, which is widely used in instrumental variable (IV) regressions. In contrast to OLS, we only estimate the causal impact of either oil, world trade, or exchange rate squared assumption errors using various instruments $\mathbf{Z}$:

$$D = \alpha_0 + \mathbf{Z}\boldsymbol{\theta} + \mathbf{X}\boldsymbol{\gamma} + u., \tag{11}$$
$$Y = \beta_0 + \beta_1\hat{D} + \mathbf{X}\boldsymbol{\gamma} + \epsilon. \tag{12}$$

In the first stage (11), instrumental variables $\mathbf{Z}$ and control covariates $\mathbf{X}$ are used to predict squared assumption errors $\hat{D}$. In the second stage (12), we use $\hat{D}$ together with the control covariates, to estimate the causal effect (β_1), under the condition that the instruments $\mathbf{Z}$ are valid.

For the selection of valid instruments, at least one instrument Z is defined for the variable of interest D, and at least one confounding covariate $\mathbf{X}$. We perform multiple 2SLS regressions with different model specifications (Table 1) to select valid instruments.[5] A valid instrument must fulfill two key conditions: (i) relevance, which means it must be sufficiently correlated with the endogenous regressor, and (ii) exogeneity, implying it must be uncorrelated with the error term in the structural equation. To assess these conditions, we employ three tests. The weak instrument test evaluates whether the instrument is strongly correlated with the endogenous regressor; under the null hypothesis, the instrument lacks sufficient correlation and is thus weak. The Wu-Hausman test (Hausman, 1978) compares the OLS and 2SLS estimators; under the null hypothesis, both estimators are consistent, but OLS is more efficient, whereas under the alternative hypothesis, OLS is inconsistent and 2SLS is preferred. The Sargan test, or J-test (Sargan, 1958), assesses the validity of overidentifying restrictions and is applicable when the number of instruments exceeds the number of endogenous variables. Including the remaining days to the target year as an additional instrument increases the number of instruments relative to the number of endogenous regressors, allowing the use of the Sargan test to examine the validity of over-identifying restrictions (see Table 1). Under its null hypothesis, the model is correctly specified, indicating that the instruments are exogenous and uncorrelated with the residuals. Therefore, our instrument selection is guided by the requirement to reject the null hypothesis

[4] In the following matrices for different variables are denoted by bold font ($\mathbf{X}$), while vectors are in normal font. Further, the vector of parameters is denoted by a bold font ($\boldsymbol{\beta}$).

[5] The 2SLS models presented in Table 1 have not been chosen for the model specification itself, but rather for the diagnostics reported.

in the weak instrument and Wu-Hausman tests while failing to reject the null hypothesis in the Sargan test, ensuring both relevance and exogeneity.

Table 1: Selection of instruments

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments: remaining days and			*Instruments: remaining days and*			*Instruments: remaining days and*		
	ASAE OP	ASAE ER	ASAE WT	ASAE OP	ASAE ER	ASAE WT	ASAE OP	ASAE ER	ASAE WT
SAE Oil Price	0.001***	0.002**	0.006***	0.001***	0.001***	0.001*	0.0001	0.0004	0.0003
	(0.0003)	(0.001)	(0.001)	(0.0002)	(0.0002)	(0.001)	(0.001)	(0.001)	(0.0003)
SAE Exchange Rates	0.337	−0.491	0.438	8.211	−0.760	−91.132	0.731	−0.110	0.646
	(1.468)	(1.724)	(1.898)	(24.916)	(2.463)	(64.705)	(1.616)	(1.833)	(1.579)
SAE World Trade	0.082***	0.080***	0.064***	0.084***	0.083***	0.080***	0.108***	0.102***	0.105***
	(0.002)	(0.004)	(0.005)	(0.002)	(0.002)	(0.006)	(0.012)	(0.020)	(0.003)
Constant	−0.129	−0.188	−0.798***	−0.333	−0.073	2.727	−0.399*	−0.316	−0.378**
	(0.149)	(0.187)	(0.232)	(0.781)	(0.154)	(2.037)	(0.218)	(0.295)	(0.161)
Observations	651	639	645	651	639	645	651	639	645
R^2	0.754	0.754	0.593	0.744	0.758	−0.718	0.706	0.729	0.718
Adjusted R^2	0.753	0.753	0.591	0.743	0.757	−0.726	0.705	0.728	0.717
Weak instruments	0***	0***	0***	0.310	0***	0.312	0***	0.015**	0***
Wu-Hausman	0.028**	0.343	0***	0.746	0.844	0.0002***	0.021**	0.320	0***
Sargan	0.447	0.751	0***	0.024**	0.325	0***	0.820	0.925	0.841

Note: *p<0.1; **p<0.05; ***p<0.01.

Besides the "remaining days" until the end of the target year, we construct instruments such as average squared assumption errors (ASAEs) and their respective lags (LASAE) to mitigate reverse causality and isolate the causal impact of assumption errors on forecast accuracy. Our findings indicate that the ASAE of oil price is a valid instrument for oil price SAE. In addition, ASAE of oil price and ASAE of world trade serve as valid instruments for world trade SAE. Further validation, shown in Appendix Table B1 to Table B7, confirms the robustness of our instrument selection (e.g., substituting remaining days with its squared version, Table B6). We exclude exchange rate SAE from the analysis because the weak instrument test fails to reject the null hypothesis, suggesting an insufficient correlation between the instrument and the endogenous variable. Thus, we treat one variable at a time as endogenous, either oil price SAE or world trade SAE. For each combination of the variable of interest and its corresponding instrument, we perform a separate 2SLS regression. In the following analysis we will not report results for LASAE, because they do not pass the Wu-Hausmann test.[6]

3.2 Machine Learning-Based Approaches

To overcome the limitations of OLS and 2SLS, and, hence, i) mitigate endogeneity issues in macroeconomic forecasting, ii) relax the restrictive linearity assumption, and iii) account for high-dimensional confounding variables while maintaining interpretability, we adopt a Partial Linear Instrumental Variable (PLIV) model within the Double Machine Learning (DML) frame-

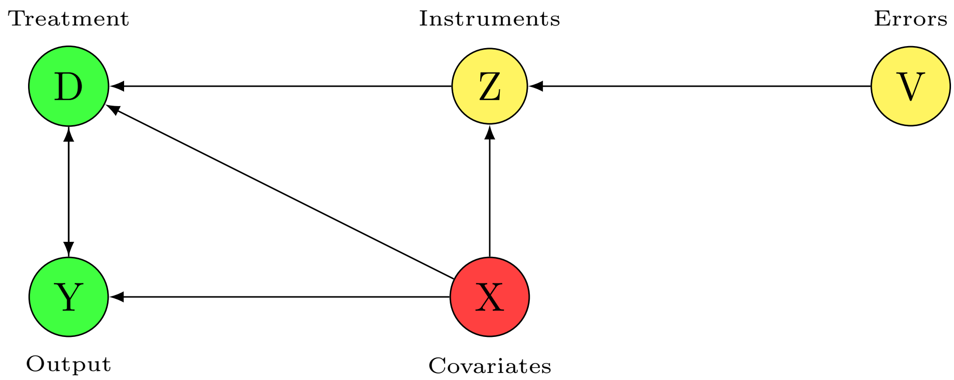
[6] See Table B8, B9 and B10 in the Appendix

work (Figure 3). [7] This approach enables a semi-parametric estimation that flexibly models the relationship between assumption errors and forecast errors. Unlike conventional machine learning approaches, which may suffer from overfitting and biased estimators for treatment effects (El-Shagi *et al.*, 2013; Beutel *et al.*, 2019), DML mitigates these issues by leveraging orthogonalization and sample-splitting techniques (Chernozhukov *et al.*, 2018). The PLIV model is given by:

$$\begin{aligned} \mathbf{Z} &= m_0(\mathbf{X}) + \mathbf{V}, \qquad & E(\mathbf{V}|\mathbf{X}) &= 0, \\ Y - D\theta_0 &= g_0(\mathbf{X}) + \zeta, \qquad & E(\zeta|\mathbf{Z}, \mathbf{X}) &= 0. \end{aligned} \tag{13}$$

Therefore, the estimation procedure consists of two stages. In the first stage, machine learning methods are applied to estimate nuisance parameters m_0 and residuals $\hat{V}$. In the second stage, estimated residuals $\hat{\mathbf{V}}$ in combination with nuisance parameter g_0 are necessary to identify the target parameter θ_0 representing the causal effect, under standard IV assumptions. For each SAE, a proper set of instruments $\mathbf{Z}$ is selected to address endogeneity concerns, along with a set of additional covariates $\mathbf{X}$ (e.g., forecast horizon, institutional-fixed effects, and year-fixed effects) (Bach *et al.*, 2021).[8]

Figure 3: PLIV model diagram



Note: Own representation.

Similarly to the 2SLS case above, the PLIV model regressions consider only one variable as endogenous in each regression and separate regressions are used for each combination of SAE and instrument. Overall, we find four valid instrument and SAE combinations to implement our PLIV model: i) SAE oil price with instrument oil price ASAE. ii) SAE world trade with instrument oil price ASAE. iii) SAE world trade with instrument world trade ASAE. iv) SAE world trade with instruments world trade and oil price ASAE. The DML technique employs cross-fitting to maintain orthogonality between estimated errors. It is based on a k-fold cross-validation approach, where the dataset is partitioned into k distinct folds or subsets. We train the model on $k-1$ folds and test it on the one remaining fold. The final model performance is generally taken as the average of the performance metrics across all k iterations, providing a more reliable assessment of the model's ability to generalize to unseen data. In particular, we

[7] The implementation of DML methods has been performed through the R package *mlr3* with *mlr3learners* extension (Lang *et al.*, 2019) and the package *DoubleML* (Bach *et al.*, 2021). The former provides access to learning algorithms necessary for implementing the models released from the latter.

[8] We report for each DML regression instrument validity in the Appendix B (from Table B1 to Table B10).

have chosen a five-fold cross-fitting for the estimation of the causal parameter θ_0. Each PLIV estimation uses the same learning algorithm for all the regressions that ultimately lead to finding $\hat{m}_0$, $\hat{g}_0$ and $\hat{\theta}_0$. Additionally, to prevent institutional imbalance across folds—where certain forecasting institutions are underrepresented—we enforce stratified random sampling, ensuring that all institutions are proportionally represented across folds. We use four machine learning algorithms, each selected for its ability to capture different functional forms and relationships: i) Random Forests (Breiman, 2001; Wright and Ziegler, 2017), ii) Decision Trees (Breiman *et al.*, 1984), iii) Gradient Boosting (Friedman, 2001; Chen and Guestrin, 2016), and iv) Lasso (Elastic Net) (Zou and Hastie, 2005; Friedman *et al.*, 2010). These learning methods have been tuned following Bach *et al.* (2021). We tune hyperparameters using grid search by minimizing the mean squared error (MSE) of the training regressions. This approach is applied to all the learners discussed above, except for the Elastic Net algorithm. For Elastic Net, a built-in function automates both the tuning process —similar to the manual grid search used for other models — and the final estimation. The regression results with optimized hyperparameters are presented in Section 4.

4 Regression results

This section presents the empirical results obtained from the estimation of double machine learning (DML) using the PLIV regression model. For comparison purposes, we also report results from the original OLS estimates of Engelke *et al.* (2019), which do not use instrumental variables or machine learning techniques. In addition, we present the results from simple 2SLS regressions that serve as an intermediary approach using traditional instrumental variable estimation. The regression results for different model specifications are reported in Figures 4 and 5.[9] The baseline specification excludes controls, capturing the total association between SAEs and forecast errors, but is vulnerable to omitted variable bias. Adding forecast horizon controls—measured in remaining days until year-end—accounts for information availability and forecast revision opportunities, which can influence forecast accuracy independently of assumption errors. Institution-fixed effects are introduced to correct for persistent, institution-specific forecasting biases that might confound the relationship between SAEs and SFEs. Year-fixed effects capture common macroeconomic shocks or trends in forecasting behavior that vary over time but affect all institutions similarly. The combined fixed effects specification includes both institutional and temporal controls, offering a more comprehensive adjustment for confounding structure, while including their interaction terms allows for modeling institution-specific temporal dynamics (e.g., changes in staff, models, or procedures) that may affect forecast quality. Together, these controls aim to improve the identification of the true causal contribution of assumption errors to forecast performance.

Across all model specifications, SAEs in world trade forecasts emerge as a significant driver of GDP forecast errors. Under OLS estimation, the squared assumption error of world trade is

[9] We report regression results in Tables C1 to C5 in the Appendix.

positively and significantly correlated with squared GDP forecast errors, explaining a substantial portion of the variation. However, when accounting for potential endogeneity using 2SLS and DML techniques, the estimated impact of SAE world trade increases in magnitude. This consistent difference suggests that OLS underestimates the causal contribution of world trade errors, likely because it fails to isolate exogenous variation in the trade forecasts. Economically, this result indicates that forecasters' ability to anticipate world trade developments is crucial for accurate GDP predictions. Errors in trade assumptions may reflect unanticipated global shocks or misjudgments about global demand, which have strong downstream effects on domestic output projections. DML methods, leveraging the ASAE of world trade or a combination of trade and oil instruments, yield significant estimates across learners. When using only ASAE oil price as an instrument for trade SAEs, the results remain significant in most cases, except under lasso, which appears more sensitive to instrument strength.

The robustness of these findings is confirmed after introducing additional controls. Adding the forecast horizon, measured in remaining days until the target year ends, does not substantially alter the magnitude or significance of the estimates. This suggests that the timing of forecast releases does not drive the observed impact of trade SAEs, but rather the quality of trade assumptions themselves. Further, controlling for institution-fixed effects-—to account for systematic biases in specific forecasting institutions—-leaves the results largely unchanged. This implies that the sensitivity to trade errors is not institution-specific but a general feature of macroeconomic forecasting. Including year-fixed effects, designed to capture time-varying economic conditions or common shocks across forecasters, produces more nuanced findings. OLS estimates decrease notably, suggesting time-fixed effects absorb some of the variation previously attributed to SAE world trade. However, 2SLS and DML estimates increase, reinforcing the idea that OLS may be biased downward in the presence of omitted variables correlated with trade errors.

In the most comprehensive specification–joint year- and institution-fixed effects in addition to the remaining days until the end of the target year–2SLS fails due to multicollinearity, underscoring its limitations in high-dimensional settings. In contrast, DML techniques continue to deliver stable and significant estimates, highlighting their flexibility and robustness. Results further support the underestimation hypothesis: even in complex model environments, SAE world trade remains a powerful and statistically significant predictor of GDP forecast error. Introducing interactions between year and institution effects to account for time-varying institutional behavior (e.g., staff turnover, model changes) does not meaningfully alter the conclusions. While the lasso learner produces an insignificant estimate when instrumenting with ASAE oil price, all other learners confirm the significant role of world trade errors. These results suggest that institutional changes do not systematically bias the causal link between trade SAEs and GDP forecast errors.

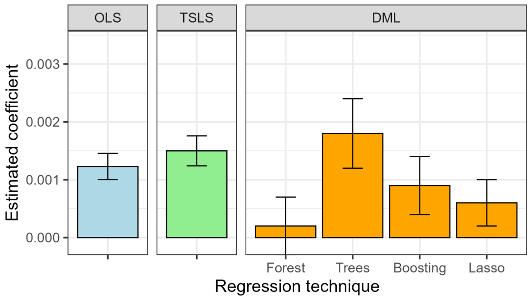
We now turn to the role of oil price assumption errors in driving GDP forecast inaccuracies. Like world trade, oil prices are a central variable in macroeconomic forecasting due to their broad impact on inflation, consumption, investment, and the external sector. Misjudging oil prices can distort GDP projections by affecting assumptions about cost structures, energy consumption, and trade balances. OLS estimates show a significant and positive impact of SAE oil price on SFE GDP, although the magnitude is modest. When applying 2SLS and DML techniques using ASAE oil price as an instrument, the estimated coefficients are slightly higher but broadly consistent. This suggests that while endogeneity may be less severe for oil price forecasts compared to trade, it still exists. Importantly, the results are stable when adding forecast horizon variables, indicating that the effect of oil price assumption errors does not depend on how early or late forecasts are issued. Likewise, controlling for institutional effects shows little variation in the results, implying that the forecast errors associated with oil prices are not tied to specific institutional characteristics.

When year-fixed effects are included, OLS and 2SLS estimates increase slightly. Among DML learners, random forest and boosting exhibit slightly larger coefficients, while lasso and decision trees yield stable estimates. These patterns suggest that oil price shocks are somewhat time-dependent and that flexible learners can capture this temporal structure more effectively. As with world trade, including all fixed effects and remaining days until the end of the forecast target year introduces multicollinearity in 2SLS models, but DML methods remain reliable. The random forest estimate declines slightly in this case, with increased standard error, whereas other learners show minimal changes. This suggests that machine learning estimators can maintain performance even in complex, high-dimensional setups.

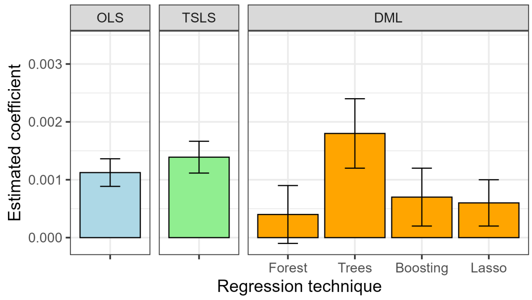
Finally, when we account for interactions between year and institution effects, the SAE oil price estimates remain significant and stable across most learners. The only exception is the random forest learner, which produces a higher coefficient, potentially capturing nonlinear interaction effects between forecasting institutions and macroeconomic shocks. Overall, the findings imply that oil price SAEs have a consistent and significant causal impact on GDP forecast errors, and that institutional dynamics do not play a major mediating role.

Figure 4: Estimation coefficients for SAE Oil Price

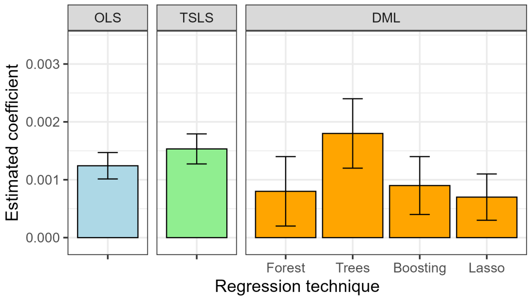
(a) Biasedness



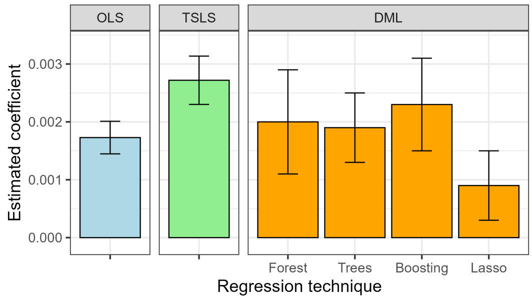
(b) Horizon in remaining Days



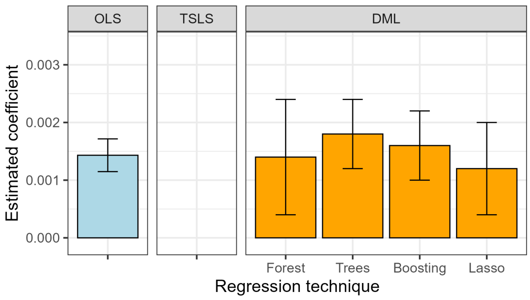
(c) Institutional-Fixed Effects



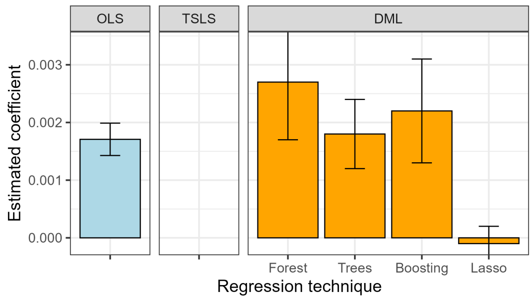
(d) Year-Fixed Effects



(e) Year- and Institutional-Fixed Effects (without Interaction)



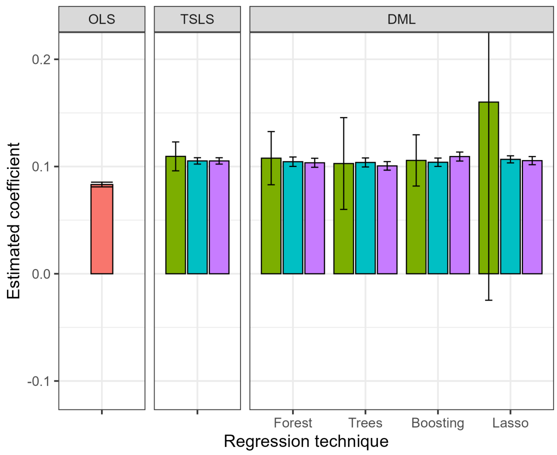
(f) Year- and Institutional-Fixed Effects (with Interaction)



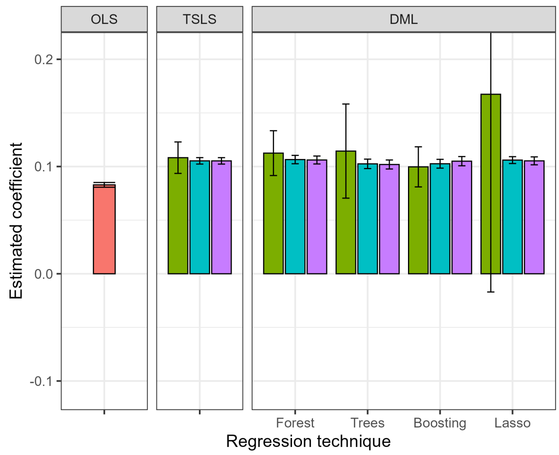
Note: Estimation coefficients are depicted for each estimation method and different estimation settings. Error bars represent the estimated standard errors.

Figure 5: Estimation coefficients for SAE World Trade

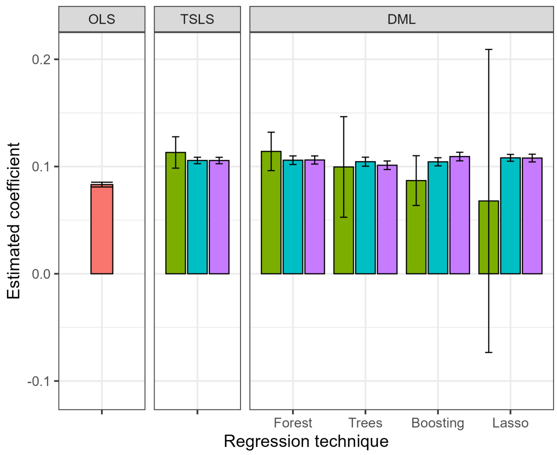
(a) Biasedness



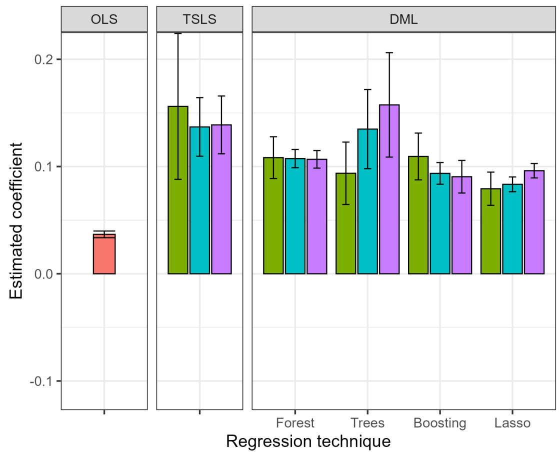
(b) Horizon in remaining Days



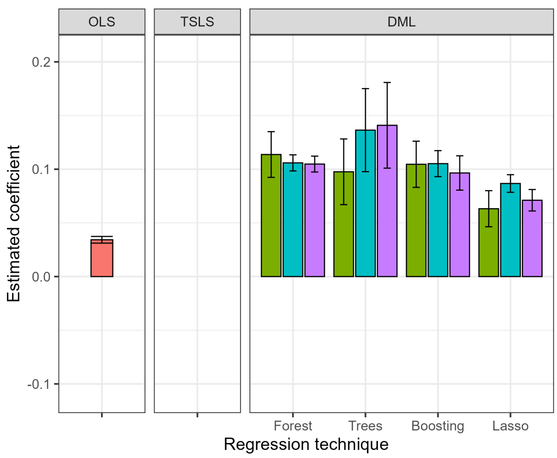
(c) Institutional-Fixed Effects



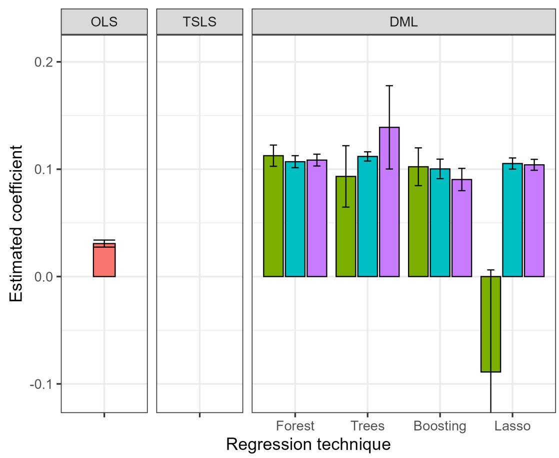
(d) Year-Fixed Effects



(e) Year- and Institutional-Fixed Effects (without Interaction)



(f) Year- and Institutional-Fixed Effects (with Interaction)



Note: Estimation coefficients are depicted for each estimation method and different estimation settings. Standard errors are depicted. Different colors represent different instruments: ASAE oil price (green), ASAE world trade (blue), ASAE world trade and oil price (purple). Error bars represent the estimated standard errors.

5 Conclusion

For forecast evaluation, the PLIV model proves to be a valuable tool for estimating causal effects in the presence of high-dimensional controls and potential endogeneity. By combining a linear component for the variable of interest with a nonparametric component for control variables, the PLIV model allows flexible modeling of complex relationships. Our findings underscore the advantages of machine learning approaches in addressing multicollinearity issues that hinder traditional estimators, such as two-stage least squares. Specifically, we demonstrate that OLS underestimates the importance of world trade for Germany's GDP, highlighting the potential of machine learning methods to control more complex functional relationships. Furthermore, our results suggest the presence of reverse causality in the relationship between assumption errors in oil price and world trade and subsequent forecast errors. This finding has direct implications for policy analysis, as it demonstrates how inaccurate assumptions can affect projections of GDP growth.

To our knowledge, we are the first study to apply the DML-PLIV framework in the context of macroeconomic forecasting to address the challenges of high-dimensional data and obtain robust estimates. First, the method leverages flexible machine learning techniques to estimate nuisance parameters, offering substantial improvements over non-parametric methods traditionally employed in semi-parametric approaches. Second, it enables statistical inference by utilizing estimating equations that adhere to the Neyman orthogonality condition and implementing a sample-splitting strategy.

Our results contribute to the discussion of weak instruments and the validity of instrumental variables in macroeconomic models. However, our diagnostic analysis identifies relevant instruments for the SAE of oil price and world trade based on the average of squared assumption errors (ASAE), suggesting that ASAE can serve as a non-weak and valid instrument.

A key insight from our results is the discrepancy between the OLS-based and DML-based estimates. In particular, OLS consistently underestimates the impact of SAE on oil price and world trade on the SFE of GDP. Although 2SLS produces estimates that vary between OLS-like and DML-like results, it suffers from significant multicollinearity issues when incorporating high-dimensional covariates. In contrast, the DML approach via the PLIV model effectively mitigates these challenges, demonstrating superior robustness in handling complex datasets with confounding variables of high dimensions. Across multiple specifications, ML techniques, such as random forests, regression trees, and LASSO, provide larger and more significant estimates compared to OLS, except for boosting methods, which exhibit less consistent significance.

Furthermore, our results regarding the SAE of the oil price deviate from previous literature. Heinisch *et al.* (2024) consistently report a positive relationship between SAE of oil price and SFE of GDP, our findings suggest that this relationship is not always positive. In several specifications, an increase in the squared assumption errors of oil price appears to reduce the magnitude of squared GDP forecast errors. However, since only a subset of negative estimates is statistically significant, the evidence remains inconclusive.

Future research should explore additional covariates and other data sets to further refine the understanding of forecast accuracy and assumption errors. In particular, the usage of text mining techniques applied to newspaper articles and social networks appears promising in enriching the information set included in the analysis. A deeper investigation into the interactions among covariates may also improve our understanding of the effectiveness of DML in resolving multicollinearity issues. In addition, analysis of forecast errors of GDP components also published by forecasting institutions could increase our understanding of the determinants of forecast accuracy.

Overall, our study advances the field of macroeconomic forecasting by integrating modern econometric techniques with ML-based estimation methods. By providing a flexible and robust framework, our approach offers valuable insights into the causal dynamics of assumption and forecast errors for improving methodologies in macroeconomic forecasting.

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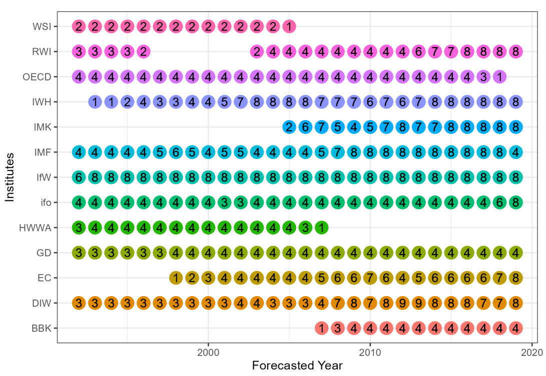
A Online Appendix

Table A1: List of Forecasters

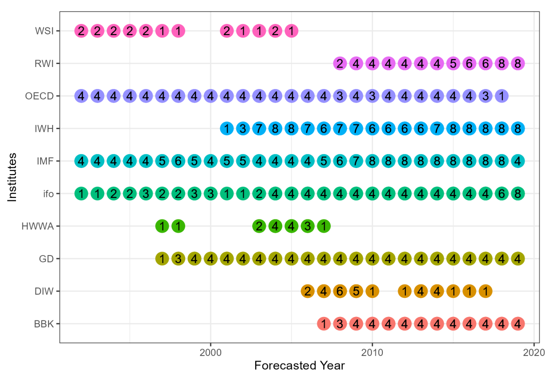
Abbreviation	Full Name
	National Economic Research Institutes
DIW	German Institute for Economic Research
HWWI	Hamburg Institute of International Economics (formerly HWWA before 2006)
IfW	Kiel Institute for the World Economy
IMK	Macroeconomic Policy Institute
ifo	Leibniz Institute for Economic Research at the University of Munich
IWH	Halle Institute for Economic Research
RWI	RWI–Leibniz Institute for Economic Research
	Joint Economic Forecast
GD	Joint Economic Forecast
	National Financial Institution
BBK	Deutsche Bundesbank
	International Institutions
EC	European Commission
IMF	International Monetary Fund
OECD	Organisation for Economic Co-operation and Development

Figure A1: Number of Forecasts

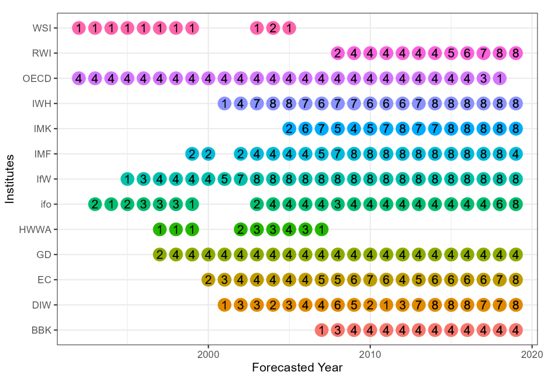
(a) GDP



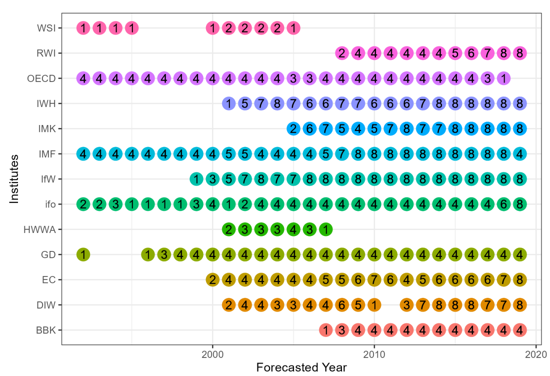
(b) World Trade



(c) Exchange Rate



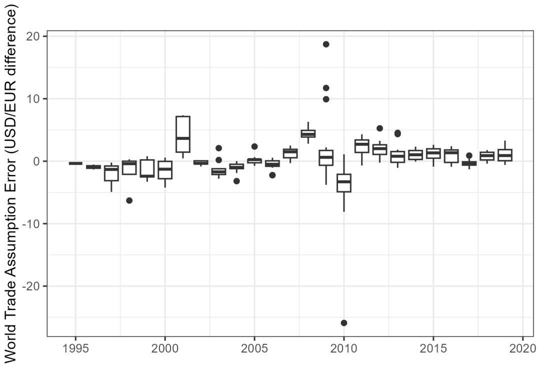
(d) Oil Price



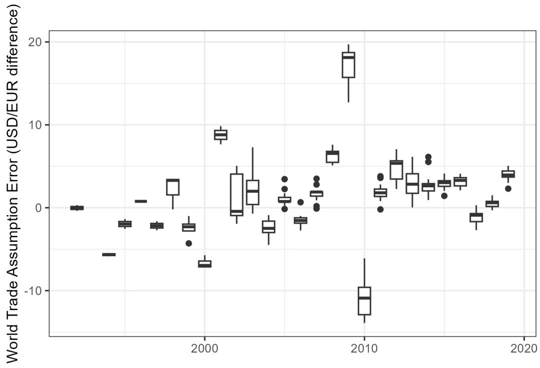
Note: Number of forecasts and assumptions analyzed for a particular target year.

Figure A2: Assumption Errors

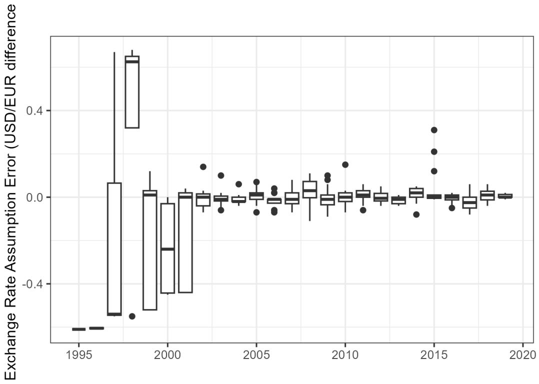
(a) World Trade Forecast Error (h=0)



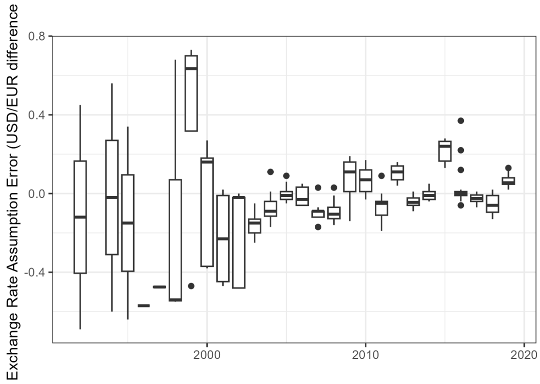
(b) World Trade Forecast Error (h=1)



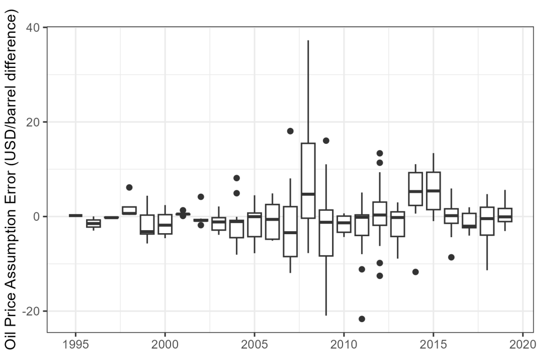
(c) Exchange Rate Forecast Error (h=0)



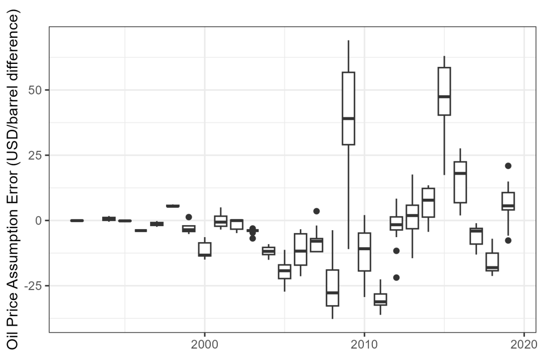
(d) Exchange Rate Forecast Error (h=1)



(e) Oil Forecast Error (h=0)



(f) Oil Forecast Error (h=1)



Note: Range of forecast errors for a particular target year conducted in the current year (h=0) or in the previous year (h=1).

Table A2: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
			Realizations				
GDP	28	1.370	1.645	−4.973	0.647	2.287	3.632
Oil Price (USD/barrel)	28	51.078	32.755	12.850	20.262	71.430	111.630
Exchange Rate (USD/EUR)	28	1.205	0.144	0.896	1.120	1.313	1.471
World Trade	28	4.750	5.128	−12.724	2.190	7.756	13.895
			Forecasts				
GDP	1,460	1.538	1.275	−6.500	1.200	2.200	4.000
Oil Price (USD/barrel)	1,159	63.864	31.560	12.000	37.250	90.000	135.000
Exchange Rate (USD/EUR)	1,123	1.230	0.208	0.430	1.120	1.350	1.850
World Trade	740	4.892	3.586	−16.500	3.500	7.000	15.000
			Forecast and assumptions errors				
GDP	1,460	0.203	1.274	−5.000	−0.300	0.600	6.800
Oil Price (USD/barrel)	1,159	−0.085	14.875	−47.730	−5.125	2.530	69.040
Exchange Rate (USD/EUR)	1,123	0.001	0.168	−0.720	−0.040	0.030	0.740
World Trade	740	1.056	4.461	−25.900	−0.805	2.752	19.720

Note: Sample 1992–2019.

B 2SLS models for instrument validity

As explained in Section 3, the importance of the estimates and the explanatory power of the model specifications reported here are limited. However, the diagnostics, reported in the lower part of the tables, guided our instrument choices. In particular, results for Weak Instrument test and Wu-Hausman test are always displayed; whereas Sargan test may not be showed. This is due to the fact that Sargan is used when testing for over-identifying restrictions (Sargan, 1958), therefore, when the number of instruments is greater than the number of regressors. Therefore, models that include one endogenous variable instrumented by a single instrument do not report the Sargan test.

Table B1: 2SLS models for instrument validity (SAE)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments:			*Instruments:*			*Instruments:*		
	both	SAE WT	SAE ER	both	SAE WT	SAE OP	both	SAE ER	SAE OP
SAE Oil Price	0.021***	0.021***	-0.007		-0.003			0.003	
	(0.002)	(0.002)	(0.03)	()	(0.017)	()	()	(0.005)	()
SAE Exchange Rates		2.294		-1645.07	-2071.53	-572.57			1.113
	()	(5.048)	()	(1736.019)	(3161.814)	(1702.808)	()	()	(1.565)
SAE World Trade			0.117			0.06	0.111***	0.043	0.111***
	()	()	(0.123)	()	()	(0.089)	(0.005)	(0.106)	(0.005)
Constant	-2.945***	-3.031***	1.103	55.04	69.525	19.169	-0.388**	0.414	-0.43**
	(0.612)	(0.642)	(4.266)	(56.194)	(105.011)	(56.722)	(0.182)	(1.263)	(0.192)
Observations	656	655	655	656	655	655	656	655	655
R^2	-2.174	-2.187	0.272	-517.735	-821.196	-62.145	0.695	0.626	0.694
Adjusted R^2	-2.178	-2.197	0.27	-518.526	-823.706	-62.338	0.695	0.625	0.693
Weak instruments	0***	0***	0.736	0.639	0.512	0.736	0***	0.512	0***
Wu-Hausman	0***	0***	0.637	0***	0***	0***	0***	0.637	0***
Sargan	0.648			0.814			0.475		

Note: *p<0.1; **p<0.05; ***p<0.01.

First, 2SLS regression models that use SAE both as regressors and as instruments are analyzed (Table B1). Therefore, we have partial model specifications where two or just one regressors are utilized, in both cases we have only one endogenous variable. Automatically excluding the endogenous variables themselves from the possible instruments, the endogenous variable is instrumented by each of the other two remaining SAE and by both of them together.

Table B2 shows models that utilize either the remaining days to target year-end, its square, or both of them as instruments for SAE. This attempt's purpose is not to demonstrate the validity of daily horizon as an instrument for SAE, but rather to verify how they could influence our diagnostics results when utilizing remaining days as a term to isolate the effects of other suitable instruments. We have utilized this method for the understanding of the Sargan test in Table 1 as well as Table B4, B6, B9 and B10.

Table B2: 2SLS models for instrument validity (remaining days)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments:			*Instruments:*			*Instruments:*		
	both	remaining days	remaining days^2	both	remaining days	remaining days^2	both	remaining days	remaining days^2
SAE Oil Price	0.002***	0.002***	0.002***	0.001***	0.001***	0.001***	0	0	0
	(0.001)	(0.001)	(0.001)	(0)	(0)	(0)	(0.001)	(0.001)	(0.001)
SAE Exchange Rates	0.751	0.735	0.749	25.18	26.877	35.628	1.045	1.025	1.132
	(1.428)	(1.42)	(1.427)	(27.307)	(27.969)	(33.375)	(1.557)	(1.546)	(1.617)
SAE World Trade	0.079***	0.079***	0.079***	0.084***	0.084***	0.085***	0.107***	0.106***	0.112***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.021)	(0.021)	(0.022)
Constant	-0.25	-0.22	-0.246	-0.911	-0.968	-1.262	-0.379	-0.364	-0.445
	(0.186)	(0.188)	(0.186)	(0.933)	(0.955)	(1.138)	(0.303)	(0.301)	(0.32)
Observations	654	654	654	654	654	654	654	654	654
R^2	0.745	0.748	0.745	0.639	0.622	0.52	0.711	0.715	0.689
Adjusted R^2	0.744	0.747	0.744	0.637	0.621	0.518	0.71	0.714	0.688
Weak instruments	0***	0***	0***	0.282	0.112	0.133	0.014**	0.004***	0.004***
Wu-Hausman	0.135	0.245	0.143	0.276	0.245	0.143	0.22	0.245	0.143
Sargan	0.415			0.275			0.27		

Note: *p<0.1; **p<0.05; ***p<0.01.

Table B3: 2SLS models for instrument validity (LSAE)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments:			*Instruments:*			*Instruments:*		
	LSAE OP	LSAE ER	LSAE WT	LSAE OP	LSAE ER	LSAE WT	LSAE OP	LSAE ER	LSAE WT
SAE Oil Price	0.05	0	0.898	0.001***	0.001***	0.002**	0	0	0.001
	(0.196)	(0.001)	(71.048)	(0)	(0)	(0.001)	(0)	(0.002)	(0)
SAE Exchange Rates	-4.189	0.396	-100.082	-46.459	1.032	-118.092	0.305	0.789	0.571
	(22.374)	(1.688)	(7961.037)	(32.096)	(1.944)	(170.129)	(1.786)	(2.052)	(1.958)
SAE World Trade	-0.121	0.08***	-3.674	0.075***	0.076***	0.072***	0.097***	0.108**	0.092***
	(0.787)	(0.006)	(296.836)	(0.004)	(0.002)	(0.008)	(0.01)	(0.054)	(0.01)
Constant	-7.519	0.13	-134.129	1.24	-0.024	2.892	-0.24	-0.393	-0.206
	(30.102)	(0.254)	(10623.293)	(0.88)	(0.156)	(4.177)	(0.202)	(0.679)	(0.195)
Observations	577	575	560	577	575	560	577	575	560
R^2	-21.931	0.705	-7401.783	0.319	0.712	-1.432	0.67	0.62	0.674
Adjusted R^2	-22.05	0.703	-7441.441	0.315	0.71	-1.445	0.669	0.618	0.672
Weak instruments	0.801	0***	0.99	0.055*	0***	0.458	0***	0.23	0***
Wu-Hausman	0.026**	0.497	0.046**	0.026**	0.497	0.046**	0.026**	0.497	0.046**
Sargan									

Note: *p<0.1; **p<0.05; ***p<0.01.

Table B3 introduces LSAE as an instrument for SAE. The Sargan test is not available due to the number of instruments being equal to the number of endogenous regressors considered. According to diagnostics results, we consider suitable instruments LSAE of oil price when considering SAE of exchange rate endogenous, but we do not report evidence of this later at Table B4, and LSAE of oil price and LSAE of world trade when world trade is considered endogenous.

Table B4 utilizes the remaining days to target year-end as an additional instrument for SAE. This is useful for obtaining the Sargan test results, which have not been shown in Table B3. We find evidence that SAE of world trade could be instrumented, according to our diagnostics, by

Table B4: 2SLS models for instrument validity (LSAE and remaining days)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments: remaining days and			*Instruments: remaining days and*			*Instruments: remaining days and*		
	LSAE OP	LSAE ER	LSAE WT	LSAE OP	LSAE ER	LSAE WT	LSAE OP	LSAE ER	LSAE WT
SAE Oil Price	0.001**	0.001**	0.002**	0.001***	0.001***	0.001***	0	0	0.001
	(0.001)	(0.001)	(0.001)	(0)	(0)	(0)	(0)	(0.001)	(0)
SAE Exchange Rates	-0.023	0.336	0.311	-19.344	1.005	-10.112	0.306	0.67	0.576
	(1.677)	(1.668)	(1.871)	(16.355)	(1.944)	(28.297)	(1.787)	(1.828)	(1.962)
SAE World Trade	0.075***	0.075***	0.072***	0.075***	0.076***	0.074***	0.097***	0.1***	0.093***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.01)	(0.023)	(0.01)
Constant	-0.036	-0.049	-0.072	0.52	-0.023	0.254	-0.242	-0.288	-0.211
	(0.189)	(0.182)	(0.194)	(0.463)	(0.156)	(0.708)	(0.202)	(0.323)	(0.195)
Observations	577	575	560	577	575	560	577	575	560
R^2	0.708	0.711	0.702	0.641	0.712	0.687	0.67	0.663	0.673
Adjusted R^2	0.706	0.71	0.701	0.639	0.71	0.686	0.668	0.661	0.671
Weak instruments	0***	0***	0***	0.024**	0***	0.277	0***	0.029**	0***
Wu-Hausman	0.694	0.655	0.538	0.187	0.514	0.703	0.025**	0.271	0.038**
Sargan	0.027**	0.303	0.046**	0.101	0.36	0.045**	0.869	0.848	0.779

Note: *p<0.1; **p<0.05; ***p<0.01.

LSAE of oil price and LSAE of world trade. However, LSAE of oil price does not seem to be a sound instrument for SAE of exchange rate anymore.

Table B5: 2SLS models for instrument validity (ASAE)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments:			*Instruments:*			*Instruments:*		
	ASAE OP	ASAE ER	ASAE WT	ASAE OP	ASAE ER	ASAE WT	ASAE OP	ASAE ER	ASAE WT
SAE Oil Price	0.001***	0	0.02***	0.001	0.001***	0	0	-0.001	0
	(0)	(0.006)	(0.005)	(0.002)	(0)	(0.007)	(0.001)	(0.013)	(0)
SAE Exchange Rates	0.337	-0.301	0.888	-261.999	-0.734	-1103.649	0.752	0.245	0.646
	(1.468)	(1.838)	(4.851)	(852.583)	(2.463)	(2463.767)	(1.633)	(4.966)	(1.579)
SAE World Trade	0.082***	0.087***	0.008	0.074**	0.083***	0.042	0.109***	0.125	0.105***
	(0.002)	(0.023)	(0.02)	(0.035)	(0.002)	(0.114)	(0.013)	(0.284)	(0.003)
Constant	-0.128	0.064	-2.778***	7.996	-0.073	34.058	-0.415*	-0.594	-0.378**
	(0.149)	(0.824)	(0.825)	(26.298)	(0.154)	(76.354)	(0.231)	(3.511)	(0.161)
Observations	647	635	641	647	635	641	647	635	641
R^2	0.754	0.75	-1.659	-11.381	0.758	-214.248	0.701	0.623	0.718
Adjusted R^2	0.753	0.749	-1.671	-11.438	0.757	-215.255	0.7	0.622	0.717
Weak instruments	0***	0.291	0***	0.756	0***	0.654	0***	0.807	0***
Wu-Hausman	0.029**	0.856	0***	0.029**	0.856	0***	0.029**	0.856	0***
Sargan									

Note: *p<0.1; **p<0.05; ***p<0.01.

Table B5 is a one-instrument version of Table 1, where only ASAE, one at a time, is taken in consideration for instrumenting SAE. We find evidence of possible instruments for SAE of oil price and for SAE of world trade. For both of them, ASAE of oil price and ASAE of world trade show small p-values for Weak Instruments and Wu-Hausman diagnostics. These results are also coherent and compatible with the ones shown in Table 1.

Table B6: 2SLS models for instrument validity (squared horizon)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments: remaining days^2 and			*Instruments: remaining days^2 and*			*Instruments: remaining days^2 and*		
	ASAE OP	ASAE ER	ASAE WT	ASAE OP	ASAE ER	ASAE WT	ASAE OP	ASAE ER	ASAE WT
SAE Oil Price	0.001***	0.002***	0.006***	0.001***	0.001***	0.001*	0	0	0
	(0)	(0.001)	(0.001)	(0)	(0)	(0.001)	(0.001)	(0.001)	(0)
SAE Exchange Rates	0.337	-0.509	0.432	14.439	-0.762	-94.441	0.757	-0.02	0.646
	(1.468)	(1.73)	(1.867)	(27.177)	(2.463)	(70.477)	(1.634)	(1.899)	(1.579)
SAE World Trade	0.082***	0.08***	0.064***	0.084***	0.083***	0.08***	0.11***	0.108***	0.105***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)	(0.007)	(0.012)	(0.022)	(0.003)
Constant	-0.128	-0.211	-0.769***	-0.525	-0.073	2.829	-0.419*	-0.387	-0.378**
	(0.149)	(0.184)	(0.226)	(0.851)	(0.154)	(2.215)	(0.222)	(0.31)	(0.161)
Observations	647	635	641	647	635	641	647	635	641
R^2	0.754	0.752	0.606	0.72	0.758	-0.827	0.7	0.71	0.718
Adjusted R^2	0.753	0.751	0.604	0.718	0.757	-0.836	0.699	0.709	0.717
Weak instruments	0***	0***	0***	0.341	0***	0.353	0***	0.018**	0***
Wu-Hausman	0.029**	0.223	0***	0.579	0.843	0***	0.015**	0.206	0***
Sargan	0.29	0.731	0***	0.027**	0.21	0***	0.954	0.946	0.93

Note: *p<0.1; **p<0.05; ***p<0.01.

Table B6 substitutes the forecast horizon in days, used in Table 1, with its square. As a second check for our choice of instruments that will be used in DML model specifications, we do not observe any differences from Table 1. SAE of oil price has one valid instrument represented by ASAE of oil price (and horizon squared in days), while SAE of world trade has two valid instruments, ASAE of oil price and ASAE of world trade (both to be considered jointly with horizon squared in days for Table B6).

Table B7: 2SLS models for instrument validity (Multiple Instruments)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments: ASAE			*Instruments: ASAE*			*Instruments: ASAE*		
	OP and ER	OP and WT	ER and WT	OP and ER	OP and WT	ER and WT	OP and ER	OP and WT	ER and WT
SAE Oil Price	0.002***	0.001***	0.018***	0.001***	0.001	0.001***	0	0	0
	(0)	(0)	(0.004)	(0)	(0.006)	(0)	(0.001)	(0)	(0)
SAE Exchange Rates	-0.821	0.285	-3.001	-1.66	-878.285	-2.016	-0.378	0.645	-0.52
	(1.723)	(1.469)	(5.384)	(2.505)	(1753.678)	(2.512)	(1.92)	(1.579)	(1.857)
SAE World Trade	0.082***	0.083***	0.014	0.083***	0.05	0.083***	0.11***	0.105***	0.105***
	(0.002)	(0.002)	(0.018)	(0.002)	(0.084)	(0.002)	(0.013)	(0.003)	(0.003)
Constant	-0.121	-0.121	-2.569***	-0.061	27.084	-0.067	-0.412*	-0.378**	-0.371**
	(0.149)	(0.15)	(0.757)	(0.154)	(54.369)	(0.155)	(0.232)	(0.161)	(0.162)
Observations	634	641	628	634	641	628	634	641	628
R^2	0.758	0.756	-1.319	0.759	-135.423	0.76	0.703	0.718	0.722
Adjusted R^2	0.757	0.755	-1.33	0.757	-136.062	0.758	0.702	0.717	0.72
Weak instruments	0***	0***	0***	0***	0.882	0***	0***	0***	0***
Wu-Hausman	0.027**	0.289	0***	0.632	0***	0.53	0.026**	0***	0***
Sargan	0.653	0***	0.232	0.028**	0.797	0***	0.796	0.733	0.808

Note: *p<0.1; **p<0.05; ***p<0.01.

Table B7 includes two ASAE at a time for instrumenting one SAE. As for previous tables, we do not find any evidence of valid instruments for SAE of exchange rate. On the other hand, we do have valid instruments for SAE of oil price, when considering a combination of oil price -

exchange rate ASAE and of exchange rate - world trade ASAE, and for SAE of world trade, in this case for any combination of two ASAE among the three considered.

Table B8: 2SLS models for instrument validity (LASAE)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments:			*Instruments:*			*Instruments:*		
	LASAE OP	LASAE ER	LASAE WT	LASAE OP	LASAE ER	LASAE WT	LASAE OP	LASAE ER	LASAE WT
SAE Oil Price	0.408	0.002	-0.015	0.001***	0.001***	0.001***	0.001**	0.002	0.001**
	(21.26)	(0.002)	(0.067)	(0)	(0)	(0)	(0)	(0.002)	(0)
SAE Exchange Rates	-13.668	-1.669	0.722	-24.517	-1.949	-32.235	0.325	-1.702	0.277
	(732.04)	(2.015)	(5.385)	(21.432)	(2.775)	(57.188)	(1.645)	(2.084)	(1.636)
SAE World Trade	-1.549	0.079***	0.146	0.08***	0.08***	0.079***	0.09***	0.073*	0.086***
	(85.195)	(0.008)	(0.27)	(0.003)	(0.002)	(0.004)	(0.008)	(0.041)	(0.008)
Constant	-60.878	-0.094	2.395	0.646	-0.029	0.855	-0.165	0.063	-0.124
	(3180.161)	(0.33)	(10.139)	(0.62)	(0.157)	(1.618)	(0.18)	(0.542)	(0.18)
Observations	608	596	600	608	596	600	608	596	600
R^2	-1316.791	0.742	-1.377	0.639	0.743	0.567	0.731	0.738	0.738
Adjusted R^2	-1323.294	0.741	-1.389	0.637	0.742	0.565	0.73	0.737	0.736
Weak instruments	0.985	0.004***	0.798	0.029**	0***	0.369	0***	0.173	0***
Wu-Hausman	0.174	0.846	0.465	0.174	0.846	0.465	0.174	0.846	0.465
Sargan									

Note: *p<0.1; **p<0.05; ***p<0.01.

Table B8 introduces the lagged version of ASAE for instrumenting purposes (LASAE). The Sargan test is not displayed, and we do not observe, as stated by the diagnostics, any valid instrument for any of the three SAEs considered.

Table B9: 2SLS models for instrument validity (Lagged Instruments, Remaining days)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments: horizon in days and			*Instruments: horizon in days and*			*Instruments: horizon in days and*		
	LASAE OP	LASAE ER	LASAE WT	LASAE OP	LASAE ER	LASAE WT	LASAE OP	LASAE ER	LASAE WT
SAE Oil Price	0.002**	0.002**	0.002**	0.001***	0.001***	0.001***	0.001**	0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0)	(0)	(0)	(0)	(0.001)	(0)
SAE Exchange Rates	0.147	-1.743	0.167	-6.31	-2.056	9.113	0.324	-1.314	0.291
	(1.622)	(1.952)	(1.635)	(13.156)	(2.773)	(23.564)	(1.645)	(2.019)	(1.638)
SAE World Trade	0.079***	0.078***	0.078***	0.08***	0.08***	0.081***	0.09***	0.094***	0.087***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.008)	(0.02)	(0.007)
Constant	-0.112	-0.132	-0.155	0.14	-0.027	-0.307	-0.164	-0.211	-0.134
	(0.187)	(0.184)	(0.192)	(0.394)	(0.157)	(0.679)	(0.18)	(0.291)	(0.179)
Observations	608	596	600	608	596	600	608	596	600
R^2	0.737	0.74	0.737	0.732	0.743	0.727	0.731	0.728	0.737
Adjusted R^2	0.736	0.739	0.735	0.731	0.742	0.725	0.73	0.726	0.736
Weak instruments	0***	0***	0***	0.009***	0***	0.223	0***	0.014**	0***
Wu-Hausman	0.509	0.351	0.383	0.616	0.803	0.698	0.176	0.468	0.392
Sargan	0.174	0.89	0.448	0.158	0.361	0.286	0.507	0.558	0.437

Note: *p<0.1; **p<0.05; ***p<0.01.

Table B9 and Table B10, respectively, add the remaining days to the target year-end and their squared version as instruments for SAE. This allows us to observe also Sargan test results. However, when considering diagnostics for these two tables, we always acknowledge the absence of any valid instruments. In particular, for all the different model specifications we cannot reject the null hypothesis of the Wu-Hausman test.

Table B10: 2SLS models for instrument validity (Lagged Instruments, Remaining days squared)

	Dependent variable: SFE GDP								
	SAE Oil Price endogenous			*SAE Exchange Rates endogenous*			*SAE World Trade endogenous*		
	Instruments: remaining days^2 and			*Instruments: remaining days^2 and*			*Instruments: remaining days^2 and*		
	LASAE OP	LASAE ER	LASAE WT	LASAE OP	LASAE ER	LASAE WT	LASAE OP	LASAE ER	LASAE WT
SAE Oil Price	0.002**	0.002***	0.002***	0.001***	0.001***	0.001***	0.001**	0	0.001**
	(0.001)	(0.001)	(0.001)	(0)	(0)	(0)	(0)	(0.001)	(0)
SAE Exchange Rates	0.143	-1.772	0.162	-4.013	-2.078	13.659	0.318	-1.244	0.293
	(1.624)	(1.956)	(1.64)	(12.792)	(2.773)	(24.153)	(1.643)	(2.059)	(1.639)
SAE World Trade	0.078***	0.078***	0.077***	0.08***	0.08***	0.081***	0.09***	0.098***	0.087***
	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.008)	(0.021)	(0.007)
Constant	-0.127	-0.148	-0.174	0.076	-0.027	-0.435	-0.16	-0.26	-0.135
	(0.183)	(0.182)	(0.189)	(0.384)	(0.157)	(0.696)	(0.179)	(0.305)	(0.18)
Observations	608	596	600	608	596	600	608	596	600
R^2	0.737	0.739	0.735	0.736	0.743	0.71	0.732	0.718	0.737
Adjusted R^2	0.735	0.738	0.734	0.735	0.742	0.709	0.731	0.716	0.736
Weak instruments	0***	0***	0***	0.007***	0***	0.22	0***	0.019**	0***
Wu-Hausman	0.391	0.258	0.27	0.741	0.795	0.555	0.192	0.37	0.387
Sargan	0.175	0.847	0.446	0.117	0.262	0.251	0.354	0.493	0.305

Note: *p<0.1; **p<0.05; ***p<0.01.

C OLS, 2SLS, DML comparison

Table C1: OLS, 2SLS, DML comparison: *Biasedness*

Model specification			SAE Oil Price	SAE World Trade
Technique	Learning method	Instrument		
OLS	—	—	0.001***	0.083***
			(0)	(0.002)
2SLS	—	ASAE OP	0.001***	0.109***
			(0)	(0.013)
		ASAE WT	—	0.105***
			—	(0.003)
		ASAE OP and ASAE WT	—	0.105***
			—	(0.003)
DML	Random Forest	ASAE OP	0	0.108***
			(0)	(0.025)
		ASAE WT	—	0.104***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.104***
			—	(0.004)
	Trees	ASAE OP	0.002***	0.103**
			(0.001)	(0.043)
		ASAE WT	—	0.104***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.101***
			—	(0.004)
	Boosting	ASAE OP	0.001*	0.106***
			(0)	(0.024)
		ASAE WT	—	0.104***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.109***
			—	(0.004)
	Lasso	ASAE OP	0.001	0.16
			(0)	(0.185)
		ASAE WT	—	0.107***
			—	(0.003)
		ASAE OP and ASAE WT	—	0.106***
			—	(0.004)

Note: *p<0.1; **p<0.05; ***p<0.01.

Note: The table presents regression results for SFE GDP as the dependent variable, with SAE Oil Price and SAE World Trade as independent variables. Various instruments and estimation techniques are applied, as detailed in the different rows. *p<0.1; **p<0.05; ***p<0.01.

Table C2: OLS, 2SLS, DML comparison: *Remaining days*

Model specification			SAE Oil Price	SAE World Trade
Technique	Learning method	Instrument		
OLS	—	—	0.001***	0.083***
			(0)	(0.002)
2SLS	—	ASAE OP	0.001***	0.108***
			(0)	(0.015)
		ASAE WT	—	0.105***
			—	(0.003)
		ASAE OP and ASAE WT	—	0.105***
			—	(0.003)
DML	Random Forest	ASAE OP	0	0.112***
			(0)	(0.021)
		ASAE WT	—	0.106***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.106***
			—	(0.004)
	Trees	ASAE OP	0.002***	0.114***
			(0.001)	(0.044)
		ASAE WT	—	0.102***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.102***
			—	(0.004)
	Boosting	ASAE OP	0.001	0.1***
			(0)	(0.019)
		ASAE WT	—	0.103***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.105***
			—	(0.004)
	Lasso	ASAE OP	0.001	0.167
			(0)	(0.184)
		ASAE WT	—	0.106***
			—	(0.003)
		ASAE OP and ASAE WT	—	0.105***
			—	(0.004)

Note: *p<0.1; **p<0.05; ***p<0.01.

Note: The table presents regression results for SFE GDP as the dependent variable, with SAE Oil Price and SAE World Trade as independent variables. Various instruments and estimation techniques are applied, as detailed in the different rows. *p<0.1; **p<0.05; ***p<0.01.

Table C3: OLS, 2SLS, DML comparison: *Institutional FE*

Model specification			SAE Oil Price	SAE World Trade
Technique	Learning method	Instrument		
OLS	—	—	0.001***	0.083***
			(0)	(0.002)
2SLS	—	ASAE OP	0.002***	0.113***
			(0)	(0.015)
		ASAE WT	—	0.106***
			—	(0.003)
		ASAE OP and ASAE WT	—	0.106***
			—	(0.003)
DML	Random Forest	ASAE OP	0.001	0.114***
			(0.001)	(0.018)
		ASAE WT	—	0.106***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.106***
			—	(0.004)
	Trees	ASAE OP	0.002***	0.1**
			(0.001)	(0.047)
		ASAE WT	—	0.104***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.101***
			—	(0.004)
	Boosting	ASAE OP	0.001	0.087***
			(0)	(0.023)
		ASAE WT	—	0.104***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.109***
			—	(0.004)
	Lasso	ASAE OP	0.001	0.068
			(0)	(0.141)
		ASAE WT	—	0.108***
			—	(0.003)
		ASAE OP and ASAE WT	—	0.108***
			—	(0.004)

Note: *p<0.1; **p<0.05; ***p<0.01.

Note: The table presents regression results for SFE GDP as the dependent variable, with SAE Oil Price and SAE World Trade as independent variables. Various instruments and estimation techniques are applied, as detailed in the different rows. *p<0.1; **p<0.05; ***p<0.01.

Table C4: OLS, 2SLS, DML comparison: *Year FE*

Model specification			SAE Oil Price	SAE World Trade
Technique	Learning method	Instrument		
OLS	—	—	0.002*** (0)	0.037*** (0.003)
2SLS	—	ASAE OP	0.003*** (0)	0.156** (0.068)
		ASAE WT	— —	0.137*** (0.027)
		ASAE OP and ASAE WT	— —	0.139*** (0.027)
DML	Random Forest	ASAE OP	0.002** (0.001)	0.108*** (0.02)
		ASAE WT	— —	0.107*** (0.009)
		ASAE OP and ASAE WT	— —	0.107*** (0.008)
	Trees	ASAE OP	0.002*** (0.001)	0.094*** (0.029)
		ASAE WT	— —	0.135*** (0.037)
		ASAE OP and ASAE WT	— —	0.158*** (0.049)
	Boosting	ASAE OP	0.002*** (0.001)	0.109*** (0.022)
		ASAE WT	— —	0.094*** (0.01)
		ASAE OP and ASAE WT	— —	0.09*** (0.015)
	Lasso	ASAE OP	0.001 (0.001)	0.079*** (0.016)
		ASAE WT	— —	0.083*** (0.007)
		ASAE OP and ASAE WT	— —	0.096*** (0.007)

Note: *p<0.1; **p<0.05; ***p<0.01.

Note: The table presents regression results for SFE GDP as the dependent variable, with SAE Oil Price and SAE World Trade as independent variables. Various instruments and estimation techniques are applied, as detailed in the different rows. *p<0.1; **p<0.05; ***p<0.01.

Table C5: OLS, 2SLS, DML comparison: *Remaining days, Inst. FE and Year FE*

Model specification			SAE Oil Price	SAE World Trade
Technique	Learning method	Instrument		
OLS	—	—	0.001***	0.034***
			(0)	(0.003)
2SLS	—	ASAE OP	[m]	[m]
			([m])	([m])
		ASAE WT	—	[m]
			—	([m])
		ASAE OP and ASAE WT	—	[m]
			—	([m])
DML	Random Forest	ASAE OP	0.001	0.114***
			(0.001)	(0.021)
		ASAE WT	—	0.106***
			—	(0.007)
		ASAE OP and ASAE WT	—	0.105***
			—	(0.007)
	Trees	ASAE OP	0.002***	0.098***
			(0.001)	(0.031)
		ASAE WT	—	0.136***
			—	(0.039)
		ASAE OP and ASAE WT	—	0.141***
			—	(0.04)
	Boosting	ASAE OP	0.002***	0.105***
			(0.001)	(0.021)
		ASAE WT	—	0.105***
			—	(0.012)
		ASAE OP and ASAE WT	—	0.096***
			—	(0.016)
	Lasso	ASAE OP	0.001	0.063***
			(0.001)	(0.017)
		ASAE WT	—	0.087***
			—	(0.008)
		ASAE OP and ASAE WT	—	0.071***
			—	(0.01)

Note: *p<0.1; **p<0.05; ***p<0.01.

Note: The table presents regression results for SFE GDP as the dependent variable, with SAE Oil Price and SAE World Trade as independent variables. Various instruments and estimation techniques are applied, as detailed in the different rows. *p<0.1; **p<0.05; ***p<0.01. The symbol **m** placed there stands for signaling the problem we have just described.

Table C6: OLS, 2SLS, DML comparison: *Remaining days, Inst. FE and Year FE, and interactions*

Model specification			SAE Oil Price	SAE World Trade
Technique	Learning method	Instrument		
OLS	—	—	0.002***	0.031***
			(0)	(0.003)
2SLS	—	ASAE OP	[m]	[m]
			([m])	([m])
		ASAE WT	—	[m]
			—	([m])
		ASAE OP and ASAE WT	—	[m]
			—	([m])
DML	Random Forest	ASAE OP	0.003***	0.113***
			(0.001)	(0.01)
		ASAE WT	—	0.107***
			—	(0.006)
		ASAE OP and ASAE WT	—	0.108***
			—	(0.005)
	Trees	ASAE OP	0.002***	0.093***
			(0.001)	(0.029)
		ASAE WT	—	0.112***
			—	(0.004)
		ASAE OP and ASAE WT	—	0.139***
			—	(0.039)
	Boosting	ASAE OP	0.002**	0.102***
			(0.001)	(0.018)
		ASAE WT	—	0.1***
			—	(0.009)
		ASAE OP and ASAE WT	—	0.09***
			—	(0.01)
	Lasso	ASAE OP	0	-0.089
			(0)	(0.095)
		ASAE WT	—	0.105***
			—	(0.005)
		ASAE OP and ASAE WT	—	0.104***
			—	(0.005)

Note: *p<0.1; **p<0.05; ***p<0.01.

Note: The table presents regression results for SFE GDP as the dependent variable, with SAE Oil Price and SAE World Trade as independent variables. Various instruments and estimation techniques are applied, as detailed in the different rows. *p<0.1; **p<0.05; ***p<0.01. The symbol **m** placed there stands for signaling the problem we have just described.

Halle Institute for Economic Research –
Member of the Leibniz Association

Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany

Postal Adress: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

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