Modelling industrial new orders using surveys

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Abstract

This paper models industrial new orders across European Union (EU) countries for various breakdowns. A common modelling framework exploits soft (business opinion surveys) as well as hard data (industrial turnover). The estimates show for about 200 cases that the model determinants significantly help in explaining new orders monthly growth rates. An alternative estimation method, new orders estimated in terms of three-month on three-month growth rates, different model specifications and out-of-sample and real-time forecasting all show that the model results are robust. We present real-time outcomes of a European Central Bank (ECB) indicator on industrial new orders at an aggregated euro area level. This indicator is largely based on national new orders data and on estimates yielded by the model for those countries that no longer report new orders at the national level. Finally, we demonstrate the leading content of the ECB indicator on industrial new orders for industrial production.

JEL classification: C22, C52, E32.

Keywords: Industrial new orders, Leading indicators, Real-time analysis, Euro area

1. Introduction

This paper models industrial new orders for EU countries for various breakdowns: total, total excluding heavy transport equipment, the main industrial groupings, and domestic and non-domestic. The model deploys various data sources. In particular, we use surveys from the European Commission’s DG ECFIN business survey in manufacturing as well as from Markit among Purchasing Managers (PMI), Eurostat’s official statistics on industrial turnover, and variables aimed at improving the model dynamics. Following the discontinuation of statistics on industrial new orders by Eurostat, we introduce an ECB indicator on new orders at an aggregated euro area level. This indicator is compiled from a mixture of national data, consisting of (1) new orders estimates obtained from the modelling framework; and, (2) hard statistics on new orders for those countries that have decided to continue the collection of industrial new orders statistics at a national level.

Modelling new orders is important, because they have historically shown to anticipate business cycle turning points and are therefore widely monitored by analysts and policy makers. There is a longstanding tradition of new orders leading industrial production (Alexander and Stekler, 1959). More recent evidence supporting the leading properties of new orders is provided by Döpke, Krämer and Langfeldt (1994) for Germany and by Garcia-Ferrer and Bujosa-Brun (2000) for France and Spain. Furthermore, new orders in manufacturing (specifically, the nondefense capital goods excluding aircraft orders sub-category) have historically exhibited high correlation with the cyclical components of the business cycle in the U.S. (Stock and Watson, 1999). Consistently, manufacturing new orders in capital goods have served as inputs to the Conference Board’s Leading Economic Index for both the U.S. and the euro area.
New orders are also among the leading series used for the widely monitored OECD’s composite leading indicator.

Notwithstanding the importance of new orders for conjunctural analysis, little literature exists that explicitly models industrial new orders and thereby could underpin our modelling exercise. We are aware of only a few studies that focus on modelling industrial new orders. Nicholson and Tebbutt (1979) draw upon early investment theories to model new orders received from the private industrial sector. They also appreciate that new orders for non-residential construction work lead the UK construction industry activity. Other studies focus on the link between business sentiment surveys and the business cycle. For example, Klein and Moore (1981) find that entrepreneur surveys on new orders are relevant for an assessment of the UK business cycle in addition to the traditional quantitative time series. More recent research concludes that business tendency surveys are able to predict the Italian business cycle, and hence are useful for forecasting the Italian real economy in the short run (Cesaroni, 2011). Etter and Graff (2003) model new orders for Switzerland using business surveys. They find that the OLS-generated estimates predict levels, turning points, peaks and troughs of their reference series very closely throughout the whole estimation period. Finally, in reaction to the ensued discontinuation of euro area new orders statistics, the European Commission (2011) analyses the relevance of EC business survey in manufacturing to the discontinued series, concluding that surveys contain relevant information for assessing the latter.

To the best of our knowledge, our study is the first to model industrial new orders by deploying qualitative and quantitative data. Given the lack of formal academic consideration as well as the small number of observations available for industrial new orders for EU countries (in some cases starting in 2003 and ending in 2012) the model is constructed by diagnostically building up on its simplest versions. Several criteria to accept the final model version are applied. Apart from statistical criteria (not only t-statistics, but also the white noise property of the model residuals), restrictions accounting for plausible economic properties (e.g. it is implausible for new orders to consistently grow faster than sales) are also considered.

The main finding of our work is that the model designed tellingly enlightens industrial new orders month-on-month (hereafter m-o-m) growth rates, which significantly benefit from the selected model determinants across all cases. In particular, turnover and surveys on new orders matter for monthly new order growth. At the euro area aggregate level, the model explains about 50% of the variation in total new orders m-o-m growth rate. The explanatory power varies for the other breakdowns of new orders considered at the euro area aggregate level between around 30% (capital goods) and 70% (intermediate goods). These are promising outcomes for the inherently noisy monthly growth rates in industrial new orders. The robustness of our model is analysed in various ways (including an alternative estimation method and different model specifications), confirming that it provides statistically as well as economically reliable outcomes, even out-of-sample and in real time.

The outline of this paper is as follows. Section 2 describes the model and its determinants and Section 3 the data. Section 4 presents the estimation results of our model including out-of-sample forecasts and explores a couple of estimation and modelling alternatives. Section 5 introduces the real-time outcome of an ECB indicator on euro area industrial new orders as well as scrutinises its forecasting properties in real time. Section 6 reports results about new orders leading production. Section 7 concludes.
2. Model

Our study pioneers modelling industrial new orders as far as scale (euro area aggregate as well as all EU countries), scope (totals, totals excluding heavy transport equipment as well as all breakdowns across main industrial groupings and origins of demand), and by deploying a broad mix of qualitative and quantitative data. Given the novelty of our modelling exercise, and due to the lack of a commonly agreed theoretical and empirical framework it could fall back on, the model determinants are drawn not only from business surveys on new orders, but also from hard data. Emphasis is thus put on ensuring that the information from a broad mixture of data sources is exploited, which should help in enhancing the robustness of the model-based proxy for new orders. The empirical framework is constructed by empirically building upon its simplest versions. The specific-to-general modelling strategy as far as the selection of explanatory variables is also sustained on the grounds of superior efficiency in terms of ex-ante forecasting performance in small samples (Herwartz, 2010).

We consider three cohorts of model determinants of m-o-m growth in new orders (NO): (i) (qualitative) surveys, (ii) (quantitative) hard data, and (iii) variables to improve the model dynamics, as summarized in Table 1:

Table 1
Overview of model determinants for euro area industrial new orders m-o-m growth

<table>
<thead>
<tr>
<th>Survey variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \text{ECFIN}$</td>
<td>Managers' assessment of the current level of order books levels surveyed on a monthly basis</td>
</tr>
<tr>
<td>$\Delta \Delta \text{ECFIN}$</td>
<td>Managers' assessment of the current level of order books levels surveyed on a monthly basis (1st difference)</td>
</tr>
<tr>
<td>$\mu \text{PMI}$</td>
<td>Manufacturing PMI new order index</td>
</tr>
<tr>
<td>$\mu \Delta \text{PMI}$</td>
<td>Manufacturing PMI new order index (1st difference)</td>
</tr>
<tr>
<td>Hard data variables</td>
<td></td>
</tr>
<tr>
<td>$TO_{m-o-m}$</td>
<td>Industrial turnover index in manufacturing (corresponds to market sales of goods or services)</td>
</tr>
<tr>
<td>$TO_{m-o-m,\text{lagged}}$</td>
<td>Industrial turnover index in manufacturing (1 period lagged)</td>
</tr>
<tr>
<td>$NO_{\text{lag}}$</td>
<td>New orders to industrial turnover ratio (1 period lagged)</td>
</tr>
<tr>
<td>Variables that improve model dynamics</td>
<td></td>
</tr>
<tr>
<td>$NO_{\text{lag,0.5}}$</td>
<td>Lagged dependent variable (by 0.5 period)</td>
</tr>
<tr>
<td>$NO_{\text{lag,1}}$</td>
<td>Lagged dependent variable (by 2 periods)</td>
</tr>
</tbody>
</table>

The first cohort of model determinants is qualitative data sources. We consider not only DG ECFIN monthly surveys in manufacturing on managers’ assessment of the current level of order books (stock concept) to be above normal/normal for the season/below normal, but also Purchasing Managers’ responses on total orders (flow concept) being higher/lower/same than one month ago. Both survey series are included in the model, with ECFIN survey as the headline survey indicator, because it is, in contrast to the PMI, available for all EU countries. To line up with the PMI survey series, which, from the conceptual point of view are preferred because they explicitly relate to new orders m-o-m growth rates, the ECFIN surveys are transformed into third differences (i.e. the three-month change). Furthermore, only the information entrenched in the PMI that is not already included in the ECFIN series is taken into account. Each survey time series is contained in the model in terms of its level as well as the first difference in order to “let the data speak” whether only levels – as expected from the conceptual point of view for the PMI – or also the change – as more expected for the ECFIN series on order book levels – matters for monthly growth in new orders.

Second, building the model empirically, from its simplest versions relying only on surveys, we find that adding quantitative statistics on sales advances the model meaningfully. The addition of sales relates to the economic accounting definition of orders, i.e. the change in order book levels results from new orders minus sales and cancelled orders:

$$\Delta \text{Order Books} = \text{New Orders} - \text{Sales} - \text{Cancelled orders}$$ (1)

The identity suggests that the model-based proxy for new orders should additionally benefit from an expression representing sales and cancelled orders. While no data on cancelled orders are available, Eurostat’s industrial turnover can be exploited to represent sales. Moreover, we enhance the model by including an industrial turnover m-o-m growth rate lagged by one period. Such an addition has a positive consequence at the country-level, because some countries release turnover late. In this way, the turnover
growth at time \((t-1)\) serves in the real-time application of the model as a proxy for sales at time \(t\), reverting to the original model, once turnover for the current reference period is released later in time. In addition, we complement the model with a one-period lagged new orders/turnover ratio to represent a long-run equilibrium relation between new orders and sales.

The third and final group of determinants assists in improving the behaviour of the model residuals. It adds to the model the dependent variable lagged by one and two periods, respectively, in order to introduce more dynamics into the model and mitigate the temporal/spatial dependence of the error term.

Our model (hereafter NOM) to estimate industrial new orders monthly growth rate for the euro area aggregate and EU countries individually reads as follows:

\[
NO_{\text{m-o-m growth}} = \beta_0 + \beta_1 \Delta_3 ECFIN_t + \beta_2 \Delta_3 ECFIN_t + \beta_3 \mu_t^{PMI} + \beta_4 \mu_t^{\Delta PMI} + \beta_5 TO_{\text{m-o-m growth}} + \beta_6 TO_{\text{m-o-m growth}} - \left(1 + \beta_7 NO_{t-1} / TO_t + \beta_8 NO_{t-1} + \beta_9 NO_{t-1} / TO_{t-1} / \mu_t^{\Delta PMI} \right) + \varepsilon_t \tag{2}
\]

The PMI residual terms are derived from extra regressions in the following fashion:

\[
PMI_t = \beta_0 + \beta_1 (\Delta ECFIN_t) + \mu_t^{PMI} \tag{3}
\]

\[
\Delta PMI_t = \beta_0 + \beta_1 (\Delta ECFIN_t) + \mu_t^{\Delta PMI} \tag{4}
\]

Eq. (2) represents the estimated NOM, whilst Eq. (3) and (4) serve as intermediate regressions from which the PMI residual terms are extracted and plugged into Eq. 2. The PMI residual terms potentially capture all extra information absent in ECFIN surveys, assuming that PMI and ECFIN surveys do not encompass identical information. All right-hand-side variables – with the exception of the lagged dependent terms and the one-period lagged new order/turnover ratio term – are expected to exhibit a positive relationship with new orders.

As stemming from freely estimated results yielded by the NOM, we estimate additional restricted specifications for the euro area aggregate and at country-level. The coefficient restrictions imposed in each case are tailored to each country’s data availability, as well as country’s individual performance under free estimation, i.e. we eliminate right-hand-side variables that showed to have little explanatory power, and limit other coefficients to ensure economic viability of their magnitudes vis-à-vis new orders monthly growth rate, e.g. new orders growth should not exceed sales growth \((\beta_6 = 1 - \beta_5)\).

3. Data

3.1 Opinion Surveys

The DG ECFIN\(^1\) survey in manufacturing measures order books, which changes can be due to new orders, completions of orders or cancellations. An increase of the indicator signals that enterprises’ stock of orders is larger than normal, which could hint to a comparatively higher order intake. The DG ECFIN’s headliner survey in manufacturing reads:

- Do you consider your current overall order books to be above normal/normal for the season/below normal?

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In contrast, the PMI surveys\(^2\) conducted by *Markit* assess new orders in manufacturing based on the following query:

- The level of total orders received this month compared with one month ago was *higher/lower/same*.

Despite the obvious methodological differences between the ECFIN and PMI surveys, the three-month change in ECFIN order books and the manufacturing PMI new orders index exhibit a pronounced co-movement and turning point alignment (see Fig. 1). Fig. 1 also plots the dependent variable, as a three-month change and in terms of the estimated m-o-m growth, illustrating the latter to be quite erratic.

![Fig. 1 Euro area surveys on new orders and total new orders growth](image)

### 3.2 Industrial Turnover

Industrial turnover measures the totals invoiced by the enterprise or kind-of-activity unit during the reference period, which corresponds to market sales of goods or services supplied to third parties. Industrial turnover includes all other charges (for example transport, packaging) passed on to the customer, even if these charges are listed separately in the invoice.

Industrial turnover can be broken down into domestic and non-domestic turnover, which requires it to be split according to the first destination of the product based on the change of ownership. The destination is determined by the residence of the third party that purchased the goods and services. The domestic market is defined as third parties residing in the same national territory as the observation unit. Non-domestic turnover is further sub-divided into turnover dispatched to euro area countries and to non-euro area countries. The turnover index is a value index with fixed base year (since 2013 2010 = 100). Its timeliness across EU countries varies between 45 to 75 days after the end of the reference month.

Fig. 2 reveals the close relationship between total new orders and total turnover in manufacturing (transformed into a 3m-o-3m growth rate, as m-o-m is too erratic to reveal the association) for the euro area. Although the statistics on industrial turnover and industrial new orders differ in terms of coverage (industrial turnover covers all manufacturing industries whereas industrial new orders cover only industries that work on the basis of orders) and in valuation (turnover is recorded at prices at times of sales whereas orders are recorded at prices at times of the order intake), the communalities are large.

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\(^2\) Results from the PMI surveys in manufacturing are available only for Germany, Ireland, Greece, Spain, France, Italy, the Netherlands, Austria ((euro area), and for Czech Republic, Poland and the UK (non-euro area). Euro area and most national data start in 1998; the series are seasonally adjusted.
4. Estimations

4.1 New Orders Model

The NOM has been estimated by OLS for all sub-groupings of new orders using euro area aggregate as well as EU country level data. The estimation results expose that all three cohorts of model determinants matter for explaining the new orders monthly growth rate, in particular, hard data and surveys, and to a much smaller extent variables to improve the model dynamics. This is evidenced by expected relationships (signified by the coefficient signs), recurring statistical significance, and by coefficients’ economically sound magnitude. Importantly, the model yields healthy residuals for the euro area aggregate and at country-level.

Table 2 reports euro area aggregate level results for all requested sub-groupings. Detailed country-level estimation results are available upon request. Regarding euro area total new orders, both free and restricted estimation explain about 50% of the variation in total new orders monthly growth rate with a corresponding standard error (SE) of regression at 1.6 percentage points (see first two rows). The restricted estimation eliminates the Δ PMI residual term, which proved to have little explanatory power, and limits turnover growth variables not to jointly exceed 1, as it is not economically viable in the long run for sales growth to exceed orders growth. Each tailored restriction set is tested for statistical viability by the Wald test and shows that the restrictions cannot be rejected (see last column). The model residuals show a satisfactory absence of correlation, as indicated by the reported Ljung-Box Q-statistics at lags 4 and 12.

Table 2
Euro area aggregate new orders: detailed estimation results across all requested sub-categories

<table>
<thead>
<tr>
<th>Sub-grouping</th>
<th>ICFN</th>
<th>Δ ECPI</th>
<th>PMI</th>
<th>Δ Resid PMI</th>
<th>Turnover growth</th>
<th>Turnover growth (Δ)</th>
<th>NO-turnover ratio (Δ)</th>
<th>Lagged dependent (1)</th>
<th>Lagged dependent (2)</th>
<th>AdjR²</th>
<th>S.E. of reg</th>
<th>p-value Q(4)</th>
<th>p-value Q(12)</th>
<th>p-value Waldχ²</th>
</tr>
</thead>
<tbody>
<tr>
<td>EA total NO (free est.)</td>
<td>0.13</td>
<td>0.13</td>
<td>0.20</td>
<td>0.10</td>
<td>0.93</td>
<td>0.34</td>
<td>-21.09</td>
<td>-0.36</td>
<td>-0.22</td>
<td>0.52</td>
<td>1.61</td>
<td>0.84</td>
<td>0.79</td>
<td></td>
</tr>
<tr>
<td>EA total NO (restricted- in-sample)</td>
<td>0.14</td>
<td>0.14</td>
<td>0.23</td>
<td>0.08</td>
<td>0.93</td>
<td>(1.45)</td>
<td>-25.28</td>
<td>-0.30</td>
<td>-0.19</td>
<td>0.10</td>
<td>1.62</td>
<td>0.60</td>
<td>0.88</td>
<td>0.34</td>
</tr>
<tr>
<td>EA total NO restricted out-of-sample</td>
<td>0.15</td>
<td>0.28</td>
<td>0.00</td>
<td>(1.25)</td>
<td>-5.05</td>
<td>-0.00</td>
<td>0.04</td>
<td>0.54</td>
<td>2.22</td>
<td>0.98</td>
<td>0.78</td>
<td>0.41</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EA NO - Capital Goods</td>
<td>0.14</td>
<td>0.15</td>
<td>0.16</td>
<td>0.15</td>
<td>0.86</td>
<td>(1.65)</td>
<td>-21.36</td>
<td>-0.27</td>
<td>0.40</td>
<td>1.14</td>
<td>0.57</td>
<td>0.25</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>EA NO - Consumer Durable Goods</td>
<td>0.17</td>
<td>0.17</td>
<td>0.27</td>
<td>0.12</td>
<td>-0.08</td>
<td>-0.08</td>
<td>-0.08</td>
<td>0.72</td>
<td>1.64</td>
<td>0.04</td>
<td>0.27</td>
<td>0.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EA NO - Consumer Non-Durable Goods</td>
<td>0.09</td>
<td>0.23</td>
<td>0.15</td>
<td>0.59</td>
<td>0.18</td>
<td>10.69</td>
<td>-0.51</td>
<td>-0.15</td>
<td>0.44</td>
<td>2.49</td>
<td>0.32</td>
<td>0.17</td>
<td>0.36</td>
<td></td>
</tr>
<tr>
<td>EA NO - Domestic Goods</td>
<td>0.14</td>
<td>0.14</td>
<td>0.69</td>
<td>(1.65)</td>
<td>-33.18</td>
<td>-0.39</td>
<td>-0.22</td>
<td>0.57</td>
<td>2.30</td>
<td>0.02</td>
<td>0.03</td>
<td>0.35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EA NO - Non-domestic Goods (EA)</td>
<td>0.14</td>
<td>0.23</td>
<td>0.22</td>
<td>0.70</td>
<td>-31.64</td>
<td>-0.43</td>
<td>-0.20</td>
<td>0.53</td>
<td>2.93</td>
<td>0.58</td>
<td>0.55</td>
<td>0.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EA NO - Non-domestic Goods (non-EA)</td>
<td>0.15</td>
<td>0.15</td>
<td>0.09</td>
<td>0.36</td>
<td>-27.56</td>
<td>-0.48</td>
<td>-0.33</td>
<td>0.41</td>
<td>1.93</td>
<td>0.58</td>
<td>0.80</td>
<td>0.92</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 2 Euro area turnover, one-period lagged new orders / turnover ratio and new orders growth
Notes: Sample period depends on data availability, which varies across variable. Bold denotes statistical significance at least at 5% confidence level. P-values Q (4) and Q (12) refer to the probability of residuals being serially correlated at lags 4 and 12 respectively.

The average goodness of the fit across the remaining requested sub-categories further corroborates the result for total new orders. We find that our model performs comparatively well for Intermediate Goods (with an adjusted R-squared of over 70%) and for the excluding heavy transport equipment sub-category (65%). Particularly the latter is in line with our expectations, as the sub-category is empirically known to more closely mirror the real economy developments, undistorted by bulky and irregular ship, railways, and aerospace orders. On the contrary, the Capital Goods sub-category comparatively underperforms with an adjusted R-squared of 30%. In terms of goodness of the fit, the remaining sub-categories oscillate around 50%. For all categories, except non-durable consumer goods, the model residuals behave correctly according to the Q-statistics. In all cases the Wald statistics show that restrictions cannot be statistically rejected.

Fig. 3 plots the actual and fitted values of the restricted in-sample estimation of euro area aggregate total new orders m-o-m growth rate. Given the inherent noise of m-o-m new order series, we find the fitted euro area aggregate values quite satisfactory, as even for monthly growth rates a close co-movement with the actual values is visible.

In order to check the validity of the NOM, we additionally estimate it for the euro area with the usual restrictions over a five-year period (1997 to 2002) and use these estimates to dynamically forecast a ten-year period (2003 to 2012) by using previously estimated values of the lagged dependent variables. Fig. 4 plots the out-of-sample forecasts of the euro area total new order index, along with the restricted model estimated for the full in-sample period, against the official Eurostat data up to March 2012. It shows that all three time series follow similar trajectories. The dynamic model forecasts for the euro area explains 97% of the variation in total industrial new orders index levels over the ten-year out-of-sample horizon. This compares to 98% for the in-sample results over the same period, and 99% for the full in-sample period. Overall, the results from the dynamic forecast exercise are supportive that the NOM generates plausible outcomes.
4.2 Alternative Specifications

To further scrutinise the validity of our model, we estimate new orders transformed into 3m-o-3m growth rate (although m-o-m growth rate is preferred, as the overall aim is to fill in monthly data gaps). As for the right-hand-side variables, all hard data are transformed correspondingly into 3m-o-3m growth rates, and the lags are also adjusted as appropriate in order to avoid any overlapping observation. Not surprisingly, going from the noisy m-o-m growth rate to the much smoothened 3m-o-3m growth rate, the goodness of the fit as measured by the adjusted R-squared improves for total new orders markedly to 0.91 from 0.52, but at the cost of an incorrect behaviour of the model residuals, as evidenced by the significant Ljung-Box Q-statistics at lags 4 and 12.\footnote{These results (and ones from forthcoming robustness checks in the current sub-section) are available upon request.} This finding is also found for the various breakdowns of euro area new orders considered.

As another robustness check, we estimated the NOM by Seemingly Unrelated Regressions (SUR) (Zellner, 1962). The gains in coefficient efficiency (as contrasted to single equation OLS estimation) can be remarkable, if explanatory variables are little correlated, whilst the disturbance terms across equations are highly correlated. Correspondingly, within the euro area context it is easy to conceive a scenario where across individual countries, factors which illuminate new orders growth are little correlated, while the portion of the variance unexplained by our model has a shared platform. The SUR results, however, turn out consistently inferior to the individual country-level OLS results. The average explanatory power is slightly lower than by OLS estimation. There are thus no efficiency gains in a system estimation compared to the single equation OLS estimations.

We also checked whether it makes sense to simplify the model by considering the “raw” PMI in terms of index level and its change rather than the applied residual approach. The underlying rationale is essentially not to omit any relevant information offered by alternative data sources even if a portion of the information found in surveys overlaps. Such approach is expected to reduce the individual regressors’ standard errors as well as those of the regression. The standard error of the regression indeed marginally declines across the majority of sub-groupings of new orders and the explanatory power (as measured by adjusted R-squared) marginally improves. However, in 7 out of the 11 sub-groupings, the simplified model version results in no impact for the ECFIN level. The latter is a strong argument in favour of the NOM, given that the ECFIN survey serves as the headline survey at the country-level for those countries for which PMI data are unavailable. Consequently, the NOM allows for a fairer comparison amongst the countries for which PMI is available and for those for which it is not.
Our final robustness check relates to adding a foreign indicator, i.e. new orders growth rates of countries that continue with the dissemination of new orders, to the NOM at the country-level. From the outset, such approach appears profligate, as it necessarily results in a unique specification for each country and/or each category for which the data collection stops. Evidently, this is at the cost of the uniform framework across countries provided by the NOM. New orders m-o-m cross-correlation matrix unveils that the “most relevant” foreign indicator for each discontinuing country at best lacks sound conceptual and empirical basis, and at worst, is arbitrary (see Table 3). The maximum correlation between the euro area countries that have discontinued the reporting on new orders and those that still release new orders varies between 0.2 for Ireland and 0.4 for Slovenia. The correlations are difficult to explain in economic terms, as for instance, Greek new orders growth appears the most relevant for those in France and Malta. Provided the lack of economic rationale, we refrain from adding the foreign indicator to the NOM, despite the fact that in three out of five cases it is statistically significant and thus enhances the goodness-of-fit.

Table 3
Euro area country-level total new orders m-o-m growth rates: cross-correlation matrix

<table>
<thead>
<tr>
<th>Discontinuing EA member-states</th>
<th>Germany</th>
<th>Spain</th>
<th>Italy</th>
<th>Netherlands</th>
<th>Greece</th>
<th>Austria</th>
<th>Belgium</th>
<th>Estonia</th>
<th>Slovakia</th>
<th>Finland</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ireland</td>
<td>0.18</td>
<td>-0.08</td>
<td>0.01</td>
<td>-0.13</td>
<td>-0.10</td>
<td>0.02</td>
<td>0.18</td>
<td>-0.02</td>
<td>0.12</td>
<td>0.02</td>
</tr>
<tr>
<td>France</td>
<td>0.16</td>
<td>0.07</td>
<td>0.31</td>
<td>0.09</td>
<td>0.29</td>
<td>0.21</td>
<td>0.09</td>
<td>0.18</td>
<td>0.21</td>
<td>0.01</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>0.22</td>
<td>0.05</td>
<td>0.07</td>
<td>0.23</td>
<td>0.20</td>
<td>0.16</td>
<td>0.31</td>
<td>0.10</td>
<td>0.15</td>
<td>0.01</td>
</tr>
<tr>
<td>Malta</td>
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<td>0.07</td>
<td>0.10</td>
<td>0.19</td>
<td>0.33</td>
<td>0.12</td>
<td>0.17</td>
<td>0.10</td>
<td>0.18</td>
<td>0.03</td>
</tr>
<tr>
<td>Slovenia</td>
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<td>0.23</td>
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<td>0.32</td>
<td>0.10</td>
<td>0.31</td>
<td>0.41</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Notes: Cyprus and Portugal are left out from the matrix for consistency reasons: total new orders series were not available at the time of conducting the robustness check.

All in all, moving from the inherently noisy m-o-m growth rates in new orders to the 3m-o-3m growth rates confirms the explanatory power of the NOM determinants, as they explain slightly above 90% of the new orders growth rates at this lower frequency. Moreover, the NOM estimates fail to improve in a statistical and/or economic way neither by system estimation nor by simplifying the incorporation of surveys nor by adding a “foreign” term at country-level.

5. Real-time results

5.1 ECB Indicator on Euro Area Industrial New Orders

Despite the discontinuation at euro area aggregate level, a number of EU countries continue the new order data collection at a national level, reflecting the importance of industrial new orders statistics for conjunctural analysis. These countries transmit the nationally collected data to the ECB. The transmitted time series are preferably seasonally and working-day adjusted, and expressed in terms of indices (from 2013 onwards base year 2010 = 100). To the best of authors’ current knowledge, Ireland, France, Cyprus, Luxembourg, Malta and Slovenia (euro area), and Denmark, Latvia, Lithuania and Hungary (non-euro area) have officially discontinued the data collection. All other EU member-countries will continue with the collection at the national level. The ECB indicator on euro area new orders combines the continued national statistics on new orders with the outcome of the NOM for those countries that have discontinued the national collection, using Eurostat’s turnover country weights with a base year 2010. Correspondingly, the euro area aggregate series consist of official hard data formerly collected by Eurostat (up to March 2012); and from April 2012 onwards, aggregates obtained from the combination of national data and the outcome of the estimation framework as described above. The ECB indicator on new orders is calculated once the incoming national data coverage reaches the Eurostat-set threshold of 60%. National data received after the euro area database is updated for a new monthly observation, replace their estimates and the euro area results are recalculated and/or revised accordingly.
Fig. 5 plots the ECB indicator for euro area industrial new orders in terms of m-o-m growth rates as well as index level up to December 2012 as available at end-February 2013.

The ECB indicator on new orders provides – unlike production data – information on the origins of demand (i.e. domestic or foreign), as illustrated for the euro area in Fig. 6. Such information is distinctive and instrumental to a comprehensive monitoring of the euro area economy, as the developments across origin might deviate. For example, non-domestic new orders were in 2012 not far away from record high levels, whereas this was clearly not the case for domestic new orders.

5.2 Real-time Forecasts

It is vital to assess whether the solution adopted for the countries that discontinue the collection of new orders is also robust in real time. To scrutinize the relationship under real-time conditions, we re-estimate the model once, up to January 2009 for the countries that have discontinued the collection of new order statistics (France, Ireland, Luxembourg, Malta and Slovenia), using historical monthly data vintages instead of the final data releases. Subsequently, we generate one-period ahead real-time forecasts for the respective countries, starting in February 2009 and ending in March 2012, i.e. 38 real-time m-o-m growth rates. This period is determined by the data availability at the country level in real time. For this reason Cyprus is missing, because no real-time data are available. To produce real-time euro area estimates, the real-time forecast results yielded at the country-level are aggregated with the new orders.
vintage data for the remainder of the euro area countries that continue to release new orders, using the Eurostat new orders weighting scheme.

As evident from Fig. 7, the ECB indicator calculated in real time closely aligns with Eurostat’s initial releases over the real-time sample period. The mean absolute error (MAE) from the real-time ECB indicator outperforms the initial Eurostat release MAE: 0.96 versus 1.00 percentage points, whereas the root mean squared error (RMSE) is in both cases 1.6 percentage points. The robustness of the model over time is further solidified at an index-level, where it becomes apparent that the real-time ECB indicator is much closer to the final Eurostat release, as compared with the initial Eurostat release, where this index is derived from cumulated initial releases of m-o-m growth rates.

All in all, the real-time exercise, albeit necessarily based on a rather short sample due to real-time data limitations at the country level, shows that the modelling approach used for the ECB indicator on euro area industrial new orders produces monthly growth rates as reliable in “predicting” the final releases for new orders as those from the initial Eurostat releases. Moreover, it shows that the index of modelling approach used for the ECB indicator on new orders is close to the index of Eurostat’s final release and clearly more accurate than the index derived from cumulating Eurostat initial releases.

Fig. 7 ECB indicator on euro area industrial new orders in real time, Eurostat initial release and Eurostat final release: m-o-m growth rate and index level

6. New Orders as Leading Series

New orders are widely monitored, mainly because of their leading properties for the business cycle. For example, new orders for capital goods have served as one of the components of the Conference Board’s Leading Economic Index for the euro area. The OECD also deploys new orders in their composite leading indicator for the growth cycle for some euro area countries, e.g. Germany. We formally analyse whether euro area new orders lead industrial production. Our results, which are robust across sub-groupings of new orders as well as two different empirical methods, indeed show that this is the case. This implies that analysts may benefit from closely monitoring the ECB indicator on euro area new orders.

The first empirical method deployed is pairwise Granger causality tests. One can refer to Granger predictability instead of causality; because Granger causality does not necessarily imply causation in the common use of this word. The ECB indicator for new orders Granger predict industrial production if current production can be explained by its own past values and the past values of new orders, and the coefficients of the lagged new orders are statistically different from zero. Table 4 shows the F-statistics of the pairwise Granger causality tests for a lag order up to 9 months (3 quarters). In case of a significant F-statistics, one statistically rejects the hypothesis that the former variable does not Granger predict the latter. The results corroborate that new orders significantly Granger predict production across all cases but not the other way around (except for the borderline results for lags 3 and 4 in the case of capital goods in log levels). Moreover, the finding that new orders lead production and not vice versa holds across all
other main industrial groupings, with the exception of non-durable consumer goods subcategory and consequently consumer goods. The latter is not surprising as orders for non-durable consumer goods have by nature a very short production time.

Table 4
Euro area new orders Granger predict industrial production

<table>
<thead>
<tr>
<th>Lag</th>
<th>Total NO → IP</th>
<th>Total IP → NO</th>
<th>Capital Goods NO → IP</th>
<th>Capital Goods IP → NO</th>
<th>Total NO → IP</th>
<th>Total IP → NO</th>
<th>Capital Goods NO → IP</th>
<th>Capital Goods IP → NO</th>
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</thead>
<tbody>
<tr>
<td>1</td>
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<td>5.0</td>
<td>82.1</td>
<td>0.1</td>
<td>16.7</td>
<td>0.2</td>
<td>8.4</td>
<td>0.0</td>
</tr>
<tr>
<td>2</td>
<td>11.0</td>
<td>2.0</td>
<td>50.4</td>
<td>3.6</td>
<td>26.5</td>
<td>0.1</td>
<td>12.4</td>
<td>0.8</td>
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<tr>
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<td>0.5</td>
<td>31.8</td>
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<td>22.4</td>
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<td>20.9</td>
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</tr>
<tr>
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<td>0.9</td>
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<td>1.5</td>
</tr>
<tr>
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<td>0.9</td>
<td>21.1</td>
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<td>12.8</td>
<td>1.0</td>
<td>19.1</td>
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</tr>
<tr>
<td>6</td>
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</tr>
<tr>
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<td>15.8</td>
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<td>0.6</td>
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</tr>
<tr>
<td>8</td>
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<td>7.1</td>
<td>0.8</td>
<td>12.9</td>
<td>1.7</td>
</tr>
</tbody>
</table>

Notes: NO = log of industrial new orders index. IP = log of industrial production index. Total NO refers to total new orders (excl. heavy transport equipment). Total IP refers to production (excl. construction). → denotes "lead". F-statistics is based on sample Jan. 1995 - Aug. 2012. Bold denotes strong evidence in favour of new orders leading production: hypothesis that the first mentioned variable does not Granger predict the second mentioned variable are rejected at 1% significance level. Cursive denotes maximum F-statistics, suggesting a peak in the leading properties of new orders.

The second empirical method deployed is an impulse response analysis based on a bivariate vector autoregressive model consisting of new orders and industrial production. The applied lag is 4 months for new orders in log levels, and 3 lags for the change in log levels of new orders. The impulse response functions depicted in Fig. 8 plot the adjustment of industrial production to an unexpected temporary shock in the level of new orders or in the change in new orders. While pairwise Granger causality tests focus on the average lead impact of new orders on production, the second method inspects the lead relationship when an unexpected change occurs. Impulse responses show that an unexpected temporary shock in new orders is followed by a significant delayed adjustment of production. The industrial production adjustment to a shock in the level of and change in new orders peaks at about 9 and 3 months, respectively. At the same time, new orders do not at all react to a shock in production (not shown in the figure).

Fig. 8 Response of euro area industrial production (excl. construction) to shock in new orders (excl. heavy transport equipment): log changes and log levels
7. Conclusions

To the best of our knowledge, industrial new orders is for the first time modelled across all EU countries and for numerous breakdowns (total, total excluding heavy transport equipment, main industrial groupings, and domestic and non-domestic, broken down into euro area and non-euro area), while applying a common modelling framework, which capitalises on a varied mix of alternative data sources (including business opinion surveys and hard data on industrial turnover). In this way, our work pioneers modelling industrial new orders as far as geographical scale, scope (numerous groupings), and varied sources of information deployed to obtain the final estimates.

Our work not merely sheds light on an under researched policy-relevant area but importantly also delivers an empirical indicator of European and international importance: the ECB indicator on euro area industrial new orders. It is compiled as an aggregation of national hard data (seasonally and working-day adjusted) being transmitted from national institutes to the ECB on a monthly basis, and estimates derived from the presented model for those countries that have discontinued the collection of industrial new orders. The publication of this indicator allows policy makers, analysts as well as academia to continue monitoring and analysing new orders at the euro area aggregate level. Our recommendation is, therefore, that the ECB indicator on euro area new orders belongs to the set of indicators to assess and monitor the state of the euro area economy. For future research on industrial new orders, our study is a useful starting point due to the surprisingly lack of other empirical studies in this field.

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References


