Estimating Bosnia and Herzegovina's Industrial Capacity Utilization Rate

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Abstract

This paper has the aim of estimating Bosnia and Herzegovina's (BIH) industrial capacity utilization. This is done by identifying capacity production as the permanent component of the BIH Index of Industrial Production via Structural Vector Autoregression. Based on theory and export orientation of the BIH industry, the identification strategy relies on the Index of Industrial Production and the PPI-based Real Exchange Rate being characterized by a joint distribution with two types of structural shocks (supply and nominal demand shocks). The results point to a large drop in average capacity after the COVID-19 pandemic-caused supply shocks, as well as the fall in industrial production in the aftermath of the Great Financial crisis being largely demand driven. The obtained measure of capacity utilization shows a similar behavior to regional survey estimates of capacity utilization in a sense that it points to a long-lasting recovery of capacity utillizations from lows achieved in the GFC.

JEL Classification: E22, E23, E32
Keywords: Capacity Utilization, Industry, SVAR model estimation

Chapter 1

Introduction and Motivation

The lack of official survey-based estimates of industrial capacity utilization (CU) creates a major bottleneck for empirical macroeconomic research into the economy of Bosnia and Herzegovina (BIH). Perhaps most significantly, any study which aims to estimate a production function of the BIH economy or industrial sector faces the challenge of possibly attributing output fluctuations due to variations in capacity utilization in industry to variations in total factor productivity, thus misidentifying trends in the productivity of the BIH economy. Thus, this paper has a practical purpose in aiming to provide estimates of capacity utilization, so that it can be used to, at least partially, mitigate this bottleneck in further research until official estimates become available.

The paper employs a structural vector auto-regression (SVAR) estimation to decompose BIH's Index of Industrial Production (IIP) into a supply (permanent) and demand (transitory) component. The supply component is taken to represent the capacity output level, and its quotient with the IIP yields monthly estimates of capacity utilization. In line with classical identification strategy related to SVAR estimation, to separate out the supply component of the IIP, we found a variable that should be influenced by the same supply and nominal demand shocks that influences the IIP. The variable we picked was the Real Effective Exchange Rate of the BIH Convertible Mark (REER), weighed by relative change Producer Price Indices between BIH and its trading partners. Given BIH's fixed exchange rate towards most of its partners, the REER essentially represents the ratio of domestic PPI to a weighed average of trading partner PPIs.

The IIP and the REER (observed monthly since Jan. 2007 until Dec. 2023) are taken to be influenced by two types of shocks, the so-called supply and demand/nominal price level shocks. It is assumed that neither type of shock has a long-run effect on the REER, while only supply shocks have a long-run effect on the IIP. Along with the assumption that these shock types are uncorrelated at all time horizons, these assumptions underlie our identification strategy.

The logic behind making the assumption of nominal shocks having a temporary effect on the IIP relies on the fact that those shocks will change the PPI-measured price levels between BIH and its main trading partners, which will temporarily boost/diminish the competitiveness of domestic industry and raise/lower output until the relative price levels adjust once more to their long-run steady state. The same can be said for BIH's REER which, due to the BAM having a fixed exchange rate to most of the trading partner's currencies, basically reflects relative changes in PPI over time between BIH and its trading partners. On the other hand, supply shocks are assumed to be inherent to the industry of Bosnia and Herzegovina and influence the IIP in a permanent manner, i.e. a positive supply shock at $t = 0$ causes an upward revision in the IIP forecast for future periods, and vice versa. Their influence on the REER is assumed to be temporary because of the law of one price taking hold in the long run between BIH and its main trading partners. The assumption of the nominal shock influencing the REER also being a valid demand shock to the IIP is further supported by the fact that exports of non-agricultural goods make up around 53.1% of the total turnover of the industrial sector of the economy as of the latest data coming from 2021 (Calculations based on Agency for Statistics of BIH's foreign trade data, and structural business statistics data).

By utilizing the SVAR method of estimation, the paper's approach relies on a number of tacit assumptions. Firstly, the IIP time series is assumed to be an observed result of a production function which describes the real output of tradable goods of Bosnia and Herzegovina's aggregated industrial sector. In this way, we make sure that the macroeconomic theory relating to production of tradable goods in a small open economy reasonably approximates the causal links that are taking place among the variables used for estimation. Secondly, the REER constructed with relative PPIs is taken to be a reasonable approximation to the terms of trade variable for the BIH economy, since the exchange rate is fixed towards the majority of the trading partners' currency. Thirdly, the REER is assumed to be a stationary process which in theory implies that it will temporarily influence the trade balance/aggregate demand in the economy. As we will later see, the hypothesis of stationarity of the REER cannot be rejected on a 95% significance level on the actual data, thus making our assumption fairly realistic.

These three assumptions underlie the theoretical underpinnings of this estimation technique and lend credibility to the estimation assumption that a shock in the REER represents a passing terms of trade shock which temporarily influences the demand that the industrial sector of Bosnia and Herzegovina is facing. They are rooted in the theoretical literature on the influence of the terms of trade on the current account balance (i.e. net demand for tradable goods faced by the industrial sector), namely in the work of Obstfeld (1982) and Svensson and Razin (1983) which came to theoretical results that the effect of a shock to the terms of trade on the current account balance of a country depends on the persistence of the perceived shock. The positive correlation of terms of trade shocks to the trade balance in the current account will be inversely proportional to the perceived persistence of the shock by the agents in the model. Hence the assumption that the REER is a stationary variable following a random walk and that the agents in the economy correctly perceive it as such, which is in line with rational expectations.

The rest of the paper proceeds as follows. Chapter 2 provides a literature review and describes the position of this paper relative to the literature. Chapter 3 describes the dataset used, the identification approach, as well as presents and discusses results. Chapter 4 concludes.

Chapter 2

Literature review

Capacity utilization measurement and estimation has featured in economic literature mainly in two strands.The first strand is consists of theoretical literature aiming to explain causes for existence and variation in capacity utilization in an economy from microeconomic and macroeconomic perspectives.

As was pointed out by Nelson (1989), the pioneering papers in terms of defining and measuring capacity utilization from an economic perspective (as opposed to the standard intuitive engineering definition) were the ones by the ones by Klein (1960), Cassel (1937), and Hickman (1964). The former's definition of capacity production entails the production level attainable at the tangency point of the long-term and the short-term average total cost curves. The second approach, expounded in the latter two papers, proposes the definition of capacity production level at which the short-term average total cost curve is at the minimum. The difference in magnitudes of capacity production in the two approaches comes from differences in the economies of scale. Under constant returns to scale, the two approaches to measuring capacity will yield the same levels of production capacity. Under increasing returns to scale in a firm, the latter approach will yield a higher capacity than the former, while under decreasing returns to scale the reverse will be the case.

On the macroeconomic theory side of the literature, a notable contribution was provided by Greenwood et al. (1988) who adopt a micro-based real business cycle approach to modelling capacity utilization inspired by theoretical considerations of Keynes (1936). In the framework they describe, a marginal productivity shock to investment (marginal efficiency of capital increase in pure Keynesian framework) induces higher capacity utilization rates, and consequently higher depreciation rates, of already installed capacity since firms seek to replace the old capital with new and more productive one as soon as possible. An approach to identifying capacity production with their theoretical results through a SVAR framework, although it has appeal, is severely constrained by the availability of data on profits (a reasonable proxy for current profitability of the installed capital stock). Such data is only available at annual frequencies, which is insufficient for a SVAR estimation on BIH data which goes back some 20 years in yearly observations.

The second strand consists of empirical literature seeking to estimate capacity utilization based on various theoretical results, with the final aim of getting to an estimate which is more consistent with our a priori theoretical beliefs of how capacity utilization should behave. This strand of literature mainly emerged to provide an alternative and improved measure of capacity utilization to the official measures published by statistical agencies.

A paper by Nelson (1989) provides a good comparison of engineering and two microeconomic definitions of capacity/capacity utilization mentioned above when they are estimated on actual data. By taking data from a panel of electric utility firm in the US from 1961 to 1983, and estimating the total cost curve equations, the paper concludes that the two economic definitions mentioned above are highly correlated with each other and with the engineering definition. The implication of such results is that administrative measures of capacity utilization might have some merit in serving as a proxy to the actual economically optimal capacity utilization.

Garofalo and Malhotra (1997) represent an empirical contribution with a similar motivation to ours as they sought to provide state-level CU estimates for the US. They employed an approach based on microeconomic theoretical literature by estimating what level of output was, on average, consistent with prevailing variable and fixed factors costs, with the assumptions that firms adjust capital to the desired level of capital with a lag of one year. What prevented the use of such an approach on BIH data was the poor availability of time series which are appropriate to represent proxies for variable and fixed costs the industrial sector is facing. Even were such data was available, it was too short in the sense of the number of observations to provide a reliable basis for obtaining sound estimates of capacity production. Similarly, Gajanan and Malhotra (2007) applied an approach to a panel of data on Indian industries between 1976 and 1996, and identified a set of trends in capacity utilizations for each separate industry.

The current paper interacts closely with a sub-strand of the empirical literature based decomposition of indices of industrial production to obtain capacity production and consequently capacity utilization. Firstly, it builds on the literature which establishes the validity of identifying the trend/permanent component of the IIP as capacity production. Namely, Kennedy (1998) established that the cycle component of IIP series in the USA showed statistical characteristics desirable of a measure of capacity utilization, mainly a good predictive power of the producer price index at various lags. This was followed by the contribution of Lalonde (1999) from the Bank of Canada, which established the SVAR as as a useful and more nuanced method of decomposing the IIP into supply (trend) and demand (cycle) components on US data. A SVAR-based approach was also used by Dergiades and Tsoulfidis (2007) who aimed to produce estimates of capacity utilization for 14 EU countries individually.

Secondly, in contrast to the Lalonde (1999) and Dergiades and Tsoulfidis (2007) papers, which use identification approaches based on CPI and aggregate profits respectively, the paper adds to the literature in terms of a novel identification approach the use of the REER to achieve identification. Given that the IIP can be thought of as an observed outcome of an unobserved production function reacting to relative prices, the justification for using REER as a variable to identify nominal shocks is that the it satisfies the conditions put forth in Blanchard and Quah (1989) for a nominal shock having a transitory effect on a real variable.

The distinct advantage of a SVAR-based approach can be summarized with the fact that it yields theory-consistent estimates of capacity utilization while requiring at most a few time series which are very often available on a monthly observation basis. These characteristics are what make this approach suitable for estimating capacity utilization of the BIH economy on which data coverage is relatively poor and/or is characterized by short time series available.

Chapter 3

Estimation of Capacity Utilization

3.1 Data Used

The estimation method employed requires two already described time series. The first among them is the deseasoned Index of Industrial Production with a base year in 2015. The series is used in its deseasoned form because any seasonal variations that are uncorrelated with demand will end up being interpreted as suppy shocks to the IIP in the SVAR estimation method. The time series was downloaded from the website of the Statistical Agency of Bosnia and Herzegovina in monthly observations from Jan. 2006 to Feb. 2024.

The second time series is the PPI-based Real Exchange Rate (base year in 2015) of the BIH Convertible Mark, observed in monthly frequency from Jan. 2007 to Dec. 2023, downloaded from Central Bank of Bosnia and Herzegovina's online database. As was previously explained, it is taken as a proxy to a terms of trade variable appearing in theoretical literature.

3.2 Statistical Tests of Utilized Time Series

In order for the SVAR estimation to be considered valid, three conditions need to be satisfied in terms of statistical properties of the time series employed.

The first among them is that all variables used need to be stationary. Of the two variables used, IIP was found to have a unit root, hence a first difference of it was done to induce stationarity. Therefore, it will enter the SVAR estimation in first difference. After the estimation is done, the supply components will have a first difference interpretation as well, hence they will be summed back together to get a time series of permanent component of the IIP. As for the REER, the hypothesis of it having a unit root is rejected on 95% significance level (see table 6.1

in the Appendix showing results of Dickey-Fuller and Phillips-Perron tests).

The second requirement in terms of statistical properties of our used time series is that they are not co-integrated, i.e. that they do not have a common trend. As the Johansen Cointegration Test shows (Appendix table 6.2), this requirement is also fulfilled.

The final requirement is more of a soft constraint which is recommended from theoretical results of Obstfeld (1982) and Svensson and Razin (1983), who reached the theoretical result that the terms of trade shock needs to be expected to have a temporary nature, in order for it to have a negative effect on the trade balance of a small open economy. This is basically a corollary to us rejecting the hypothesis of the REER having a unit root. Of course, we are assuming that the agents in the economy have rational expectations and recognize the stationarity of the REER.

3.3 Identification Approach

As was previously mentioned, the estimation method we will employ for isolating the permanent component of the IIP time series (taken as capacity) is a basic structural vector autoregression (SVAR). The variables which will be used are the first difference of the Index of Industrial Production (IIP) and the PPI-based Real Exchange Rate of the BIH Convertible Mark (REER).

Our identification approach rests on a few pillars which ensure identification. Firstly, consistent with the approach in Blanchard and Quah (1989), we assume two types of shocks which simultaneously effect the IIP and the REER. The first shock (supply shock) is taken to have no long-run effect on the REER, while it can have a long-run effect on the IIP. The second shock (demand/terms of trade shock) has no long run effect on either the IIP or REER. The shocks are taken to be uncorrelated at all leads and lags.

The assumption of the IIP and REER being influenced by these two shocks simultaneously were made based on theory, as well as statistical data on Bosnia and Herzegovina's industrial sector turnover. Firstly, as was previously mentioned, non-agricultural goods make up about 53.1% of total industrial turnover as of 2021. This gives us good reason to believe that the time series of industrial production and relative price levels are jointly distributed. Secondly, given that BIH's PPI-based REER is basically a quotient of the weighed average of trading partner PPIs and the domestic PPI, it essentially represents a nominal variable on the price competitiveness of BIH exports. As such, in line with macroeconomic theory, it cannot have a long-term effect on a real variable such as aggregate demand which influences the IIP. However, a demand or a supply shocks which influences it have transitory effects on it since they operate in the short term until the law of one price starts taking hold between BIH and its trading partners. A similar logic holds for demand and supply shocks influencing the IIP. A nominal demand shock will influence it temporarily as prices on its inputs and outputs become fully flexible in the long-run, while supply shocks are understood as influencing the IIP in a permanent manner (a positive supply shock in time $t = 0$ causes an upward revision in the forecast for all future periods) because they enable more production at same price levels.

Given that both of the variables we are using are stationary, and given the assumptions above, assuming $P_t = (\Delta IIP_t, REER_t)'$, and $\epsilon_t = (\epsilon_s, \epsilon_d)'$:

$$P_t = \sum_{i=0}^{\infty} A(i)\epsilon_i \tag{3.1}$$

Where the sequence of matrices A is such that its $a_{11}(i)$ element sums to zero for $i = 1, 2, 3, ...$ This assumption insures that ϵ_d has no long-run effect on the level of IIP since it enters the model in first difference. An additional assumption is that $Var(\epsilon) = I$. Since the shocks are assumed to be uncorrelated at all leads and lags, their variance-covariance matrix is diagonal and can be normalized to identity matrix for simplicity.

Equation (3.1) is therefore the structural model of the joint distribution of IIP and REER which we have assumed. The problem is that it is unobserved and that we have to infer it from the data. The starting point is the Wold moving-average representation of this bivariate stochastic process which exists due to the stationarity of P_t:

$$P_t = e_t + C(1)e_{t-1} + ... = \sum_{i=0}^{\infty} C(i)e_i \tag{3.2}$$

From here, upon comparison of (3.1) and (3.2), we see that $e = A(0)\epsilon$ and that $A(i) = C(i)A(0)$ (for $i = 1, 2, ...$), which allows for identification of the matrix $A(0)$, which allows for the estimation of the history of supply and demand shocks. For a rigorous proof, see Blanchard and Quah (1989).

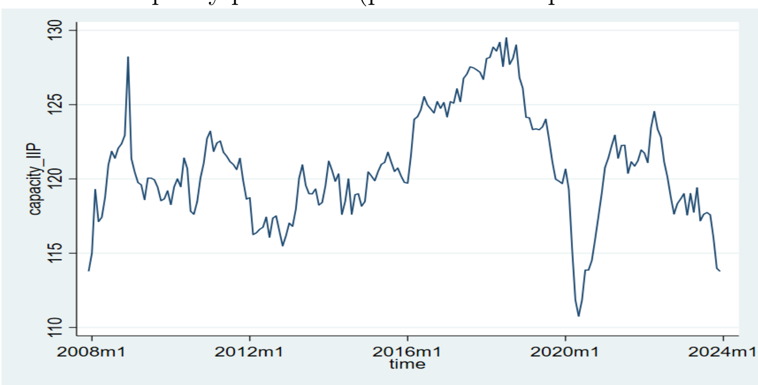
The number of lags we chose to include in the underlying VAR model is 12, due to practical reasons. Our optimal lag selection points to selecting an optimal lag of 2, and although this is optimal given the statistical properties of the data in the sample, we have theoretical reasons to believe that the price adjustment process lasts for longer than two months and hence the effects of a demand or supply shock will take longer to materialize. Given that our sample is long enough, we saw it as innocuous to add more lags, longer horizons were avoided due to the risk of over fitting. Since we are dealing with variables observed in monthly measurements, these problems will be mitigated with time as the length of the observed time series lengthens.

Once we have obtained the sequence of supply shocks to the IIP, it is necessary to sum back the estimated shocks in order to obtain the cumulated capacity equivalent of the IIP. However, the capacity estimated needs to be anchored on some level, for this we use the World Bank Enterprise survey which estimated 81.6% capacity utilization in 2023 in BIH's manufacturing sector. Thus, we assumed that capacity equaled $IIP/0.816$ in Oct. 2023. This was our anchoring point for the capacity estimates, from there we added the history of the estimated supply shocks to obtain the full time series for production capacity. From there, the capacity utilization time series was obtained by dividing the IIP with capacity production, i.e. $CU_t = \frac{IIP_t}{CAP_t}$.

3.4 Results and Discussion

The estimated capacity time series obtained as was described above, are plotted in Figure 3.1 below. As can be seen, although with considerable volatility, estimated capacity production had a stable mean in the pre-2016 period. This was followed by fairly quick growth of estimated capacity from 2016 to the end of 2019. Furthermore, the COVID-19 pandemic-related supply shocks were very large in magnitude and caused a significant drop in estimated capacity production from which no recovery was made as of yet.

Figure 3.1: Estimated capacity production(permanent component of the deseasoned IIP)

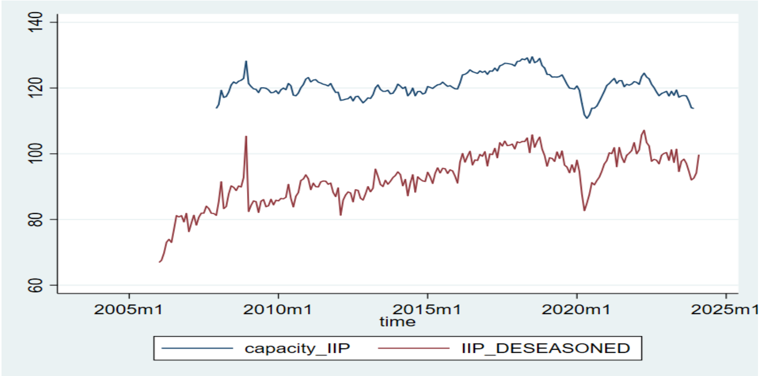


Source: Own estimates

When we plot the IIP and the estimated capacity IIP together (Figure 3.2), we can see that they largely follow each other well and that the capacity production is more stagnant than the IIP time series.

Our final result is presented in Figure 3.3, where the estimated capacity utilization series is provided. The tabular version of the results is available in the Appendix. Given that the estimated capacity time series was more stagnant than the deseasoned IIP, we see a mild upward local trend in CU between 2009 and 2016, meaning that a lot of IIP growth in the IIP in those years is estimated to be driven by growing capacity utilization in industry. This points to

Figure 3.2: Estimated capacity production and deseasoned IIP



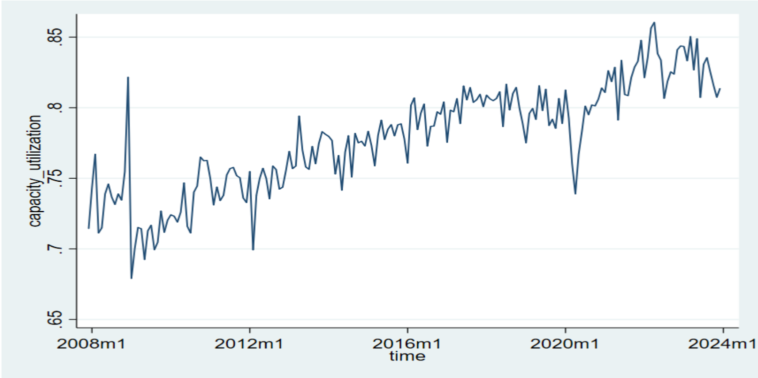
Source: Own estimates and BIH Agency for Statistics

the estimate that the 2009 recession, and the turmoil associated with the European sovereign debt crisis that followed causing prolonged deviations from normal capacity utilization. The implication of the joint occurrence of capacity utilization rising from low levels, and more or less stagnant capacity is that the crises in this period manifested themselves mostly as demand shocks.

From 2016 to the end of 2019, we see a largely stable estimated capacity utilization, which was followed by a steep and short drop in utilization during the COVID-19 pandemic-induced lock downs.The aftermath of the COVID-19 crisis brought with it higher capacity utilization rates which are estimated to be around record highs. This is both a result from strong demand, and lower capacity production induced by the COVID-19 crisis supply shocks. The clear corrolary conclusion which we can derive from these findings is that the COVID-19 pandemic-related crisis manifested as a joint occurrence of a large supply and demand shocks, whith the former being dominant. This was followed by positive demand shocks in the recovery period, with supply shocks to the IIP being very mixed, presumably due to an unfavorable investment climate and outlook in the industrial sector.

As a final comparison and soft form of a robustness check, it is useful to see the official survey-based estimates of industrial capacity utilization for Western Balkans countries. These are plotted in Figure 3.4, on which we see the results for Serbia and Croatia separately, as well as the regional average capacity utilization calculated as a simple arithmetic mean of capacity utilizations in Croatia, Montenegro, North Macedonia, and Serbia. Albania was not included in the regional mean since it has a significantly shorter sample of observations which would make it impossible to calculate a sufficiently long time series for average regional estimated capacity utilization. What unites these estimates with ours is that there is an evident mild trend in regional and BIH estimates, which is also true for Croatia and Serbia observed individually.

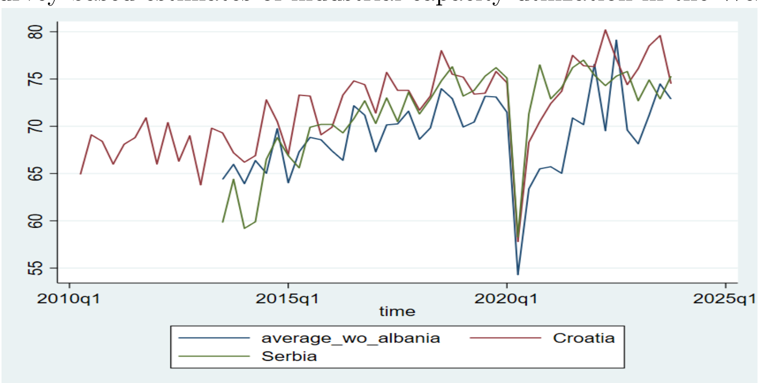
Figure 3.3: Estimated capacity utilization in BIH's industrial sector



Source: Own estimates

The only significant difference in the regional administrative and our estimates is that they show a much larger dip in capacity utilization as a consequence of the COVID-19 pandemic. This is of course a direct consequence of the model which ascribed much of the shock to a supply shock, since the fall in REER was not on average commensurate to the fall in deseasoned IIP, based on average behavior of these variables in the sample.

Figure 3.4: Survey-based estimates of industrial capacity utilization in the Western Balkans



Source: Eurostat

Chapter 4

Conclusion

This paper presented a novel way of estimation capacity utilization in the industrial sector based on the SVAR method of estimating a permanent component of a time series. The final aim was providing a reasonably reliable estimate of CU until an official one become available. Overall, the estimated time series captures the more or less expected cyclicality. Along with approximating the regional capacity utilizations well, the obtained estimates have as structural interpretations in a sense that we derive the capacity IIP which is consistent with the long-term balance in purchasing power parity between BIH with its largest trading partners.

With the industrial capacity utilization estimate being now available in a reasonable long time series (approximately a 15 years-long sample of monthly observations), we hope this research temporarily fills the gap in missing official data on the capacity utilization in the industrial sector until more precise administrative and/or statistically modelled estimates become available. To the best of our knowledge, similar estimates which rely on statistical methods of estimation of capacity utilization do not exist for Bosnia and Herzegovina's Western Balkans peers.

Further work on this topic is possible in a couple directions. Firstly, as a form of a robustness check of the estimates obtained, it would be useful to replicate the estimate on the data from comparable Western Balkans economies and see how well do they replicate the official survey-based estimates that exist for those countries. Secondly, SVAR models of estimation are not limited to including just two variables, therefore the inclusion of an additional variable that would improve estimation based on some theory-based expectation might be a possible advance. However, given that the number of parameters to be estimated rises exponentially as additional variables are added, adding more variables runs a significant risk of inducing overfitting in a model with just around a couple of hundred of monthly observations, so this sort of an advance might be feasible in the future as more observations accumulate.

Chapter 5

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Chapter 6

Appendix

6.1 Relevant Statistical Tests

Table 6.1: Unit root test resutls

	(1) Dickey-Fuller Test test statistic/p-value	(2) Phillips-Perron Test test statistic/p-value
First difference of IIP (216 observations)	-20.495 0.0000	-22.181 (Z(t)) and -255.908 (Z(rho)) 0.0000
PPI-based REER (203 observations)	-3.029 0.0322	-3.342 (Z(t)) and -21.377 (Z(rho)) 0.0131

Table 6.2: Johansen tests for cointegration of IIP and REER

Rank	(1) Trace Statistic	(2) Critical value for 5%
0	44.4813	15.41
1	14.4699	3.76

6.2 The CU Time Series

The author will be updating the time series for CU estimations on a regular basis. If you need it for research purposes, please contact the author for a csv or Excel workbook version, please contact the author.

Year	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
2007	-	-	-	-	-	-	-	-	-	-	-	71.41
2008	74.31	76.71	71.13	71.49	73.89	74.6	73.68	73.15	73.9	73.46	75.47	82.16
2009	67.91	70.0	71.52	71.43	69.25	71.29	71.68	69.95	70.47	72.68	71.17	72.04
2010	72.42	72.32	71.9	72.61	74.69	71.6	71.13	74.02	74.46	76.51	76.24	76.27
2011	74.97	73.11	74.39	73.43	73.8	75.24	75.69	75.77	75.19	75.04	73.61	73.28
2012	75.48	69.94	73.79	74.98	75.72	74.99	73.55	75.87	75.62	74.24	74.38	75.57
2013	76.91	75.69	75.87	79.41	77.01	75.81	75.64	77.26	76.03	77.48	78.31	78.12
2014	77.97	77.68	75.31	76.62	74.16	76.86	78.02	75.09	78.18	77.52	77.62	77.29
2015	78.33	77.32	75.88	78.04	79.13	77.75	78.48	78.8	78.01	78.79	78.86	77.79
2016	76.07	80.18	80.7	78.45	79.61	80.26	77.28	78.68	78.7	79.71	79.54	80.41
2017	77.55	79.83	79.72	80.64	78.88	81.55	80.56	81.43	80.38	80.57	80.95	80.08
2018	80.89	80.64	80.5	80.66	81.13	78.66	81.67	79.85	81.01	81.44	79.98	78.86
2019	77.51	79.59	79.95	79.17	81.56	79.8	81.32	78.74	79.18	78.55	80.65	78.88
2020	81.25	79.26	76.05	73.9	76.7	78.35	80.12	79.51	80.2	80.13	80.62	81.4
2021	81.09	82.62	81.85	82.86	79.13	83.36	80.94	80.86	82.15	82.88	83.29	84.78
2022	82.13	83.55	85.65	86.05	83.83	83.37	80.66	81.86	82.54	82.38	84.11	84.37
2023	84.34	83.33	85.04	82.67	84.9	80.73	83.08	83.54	82.54	81.6	80.74	81.39

Table 6.3: BIH Industrial Capacity Utilization Estimates by Year and Month (in %)