ASSESSING MODELS FOR DEMAND ESTIMATION: EVIDENCE FROM POWER MARKETS

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Overview

The estimation of demand elasticities represents an important and well-established method among economists. It is used within a range of policy-relevant applications, such as in evaluating market power or merger effects. Yet, obtaining precise estimates can be challenging due to unobservability of data and endogeneity concerns. Apart from cases where demand and supply data can be simulated (e.g. Semadeni et al., 2014), the resulting estimates of elasticity in general cannot be validated.

In some rare cases, however, the demand curve and thus its elasticity is directly observable. Using real-world data on revealed demand curves on power markets, we investigate the validity of the traditional Instrumental Variable (IV) approach for estimating demand elasticities, as well as various novel machine learning techniques. In particular, we explore how Lasso regression can be combined with IV in order to attain both, an optimal model selection and an amelioaration of the endogeneity problem inherent to price-quantity regression settings.

The IV estimator has become a standard tool to estimate demand in a wide range of markets. However, it is particularly well-suited in the power market context, where due to the homogeneity of electricity, possible substitution patterns (e.g. as in Berry et al., 1995) can be ignored (for a detailed study on demand estimation in power markets see Lijesen, 2007). Despite their long-standing history (see Angrist and Krueger, 2001), IV demand estimation techniques have recently in part been advanced by machine learning tools (e.g. Bajari et al., 2015), especially applicable to study binary treatments. Therefore, we consider both the classic IV demand estimation techniques and a novel Lasso-based two staged estimator.

Methods

All empirical demand estimation methods are applied to high-frequency German-Austrian power market data. The power market is an ideal candidate for our study, since the demand curves from multi-unit double auctions are directly observable, which allows us to compute the “true” elasticity of demand as represented by the bids. We use bid data from the day-ahead market and construct this underlying elasticity by considering individual bid curves for each of the 24 hourly products. We then fit a log-log model to the demand curve, which yields an isoelastic demand function, see Figure 1. Subsequently, this “true” elasticity can be compared to our IV and Lasso estimators.

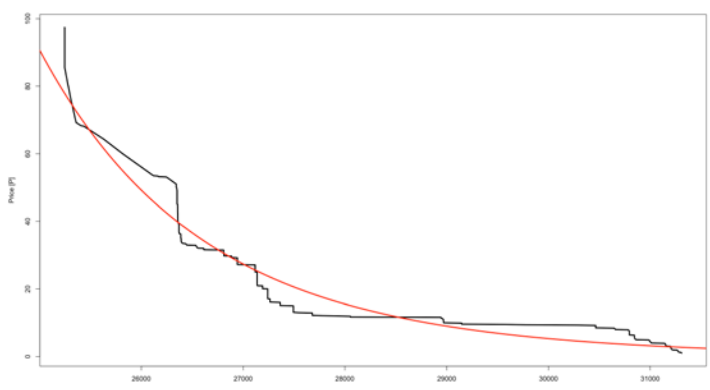

Figure 1: True bid curve with isoelastic demand, 01.01.2014

Having obtained coefficients on the elasticity of the original demand curves, our empirical strategy proceeds as follows: We apply the standard IV approach from the literature. In contrast to using the revealed demand curve, the estimation here is based on equilibrium prices and quantitites, which in many standard cases of demand elasticity estimation is the only data available. As instruments, respectively supply shifters, we rely on a number of variables such as hourly wind and solar infeed, as well as the total infeed from renewable source, prices of conventional energy sources and hourly total load. Finally, we compare the IV estimates of the demand elasticity to the true underlying submitted demand curves and construct measures for assessing the precision of the IV estimator. We repeat this sequence for peak and off-peak data to understand the workings of the IV estimator for both off-peak and more inelastic peak hours. Further, we employ Lasso as a first-stage procedure in the 2-stage-least-squares for computing the instrumentalized dependent variable and check whether this approach yields better results compared to OLS. We further show a possible approach to compute standard errors in this setting. We also run a naïve OLS controlling for total system load as a proxy for demand shifts.

Results

We find the yearly average elasticity of the demand curves to be -0.39 for peak hours and -0.37 for off-peak hours. Our results show that for IV estimation models, the best performance can be achieved by employing the total renewable feed-in as instrument and controlling for hours, which results in fairly accurate estimate of -0.37 and -0.39 for peak and off-peak hours, respectively. This model outperforms all other IV-models, including those controlling for total load, coal and gas prices, seasons and many others. The second best approach is the naïve OLS with a control for “Load” only. Further, we observe that using either the wind feed-in or the solar feed-in as instruments provides a lot of variation and unreliable results. In particular, the estimates can deviate up to twofold depending on the choice of the control variables. Using the total feed-in yields more consistent results. In addition, we show that using Lasso models for the first-stage in 2SLS, the estimates achieved by the optimal IV model cannot be further improved. Furthermore, we find that for IV models, there are no substantial differences between modelling peak and off-peak hours, i.e. the best model choice for peak hours delivers very precise estimations for off-peak hours as well. By conducting a monthly estimation of the elasticities, we show that depending on the season, the OLS controlling for Load model outperforms the IV model and vice versa. Apart from that, in particular the summer months show a lot of variation making it difficult to properly estimate the elasticity yielding higher standard errors.

Conclusions

Demand estimation techniques are an integral part in the standard toolbox of energy, industrial and competition economists. Assessments of pricing and investment decisions, merger effects or policies to foster demand flexibility all require information on the demand side. Whereas IV estimation is often used to inform reseachers, policymakers and industry on market demand, there are no detailed tests of this technique that rely on real-world data and shed light on its actual performance and possible caveats. In particular, since the true demand curve is in general unobservable, there is no way to assess the goodness of the calculated estimates. In this paper, we make use of detailed power market data to assess the quality of various demand estimation techniques. We utilize the fact that true bid curves are observable and use these observations for comparing the estimates and the deviations from the true demand elasticity. Our conclusion is twofold: Firstly, the established IV models perform very well on the power market when employing total renewables feed-in (joint wind and solar generation) as instrument and combining this with the right control variables. The differences for peak and off-peak hours are insignificant, meaning that there is no need for separate models. Secondly, we observe that depending on the choice of the instrument variable, the suitable controls are hard to find and pose a problem for the variance of the estimated coefficients. We also find that IV methods cannot be outperformed by a including a first stage Lasso regression technique. Future work could shed more light on the workings of Lasso-based IV methods within smaller samples.

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