



# Assessing Models for Demand Estimation Evidence from Power Markets

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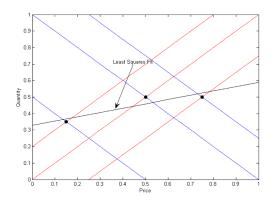
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  - Suitable IV data available
- → Relevant for both: general IO and Energy research

#### Contents



- Motivation
- Framework for model assessment
- Empirical setup
  - Estimating demand elasticity from bid curves
  - Estimating demand elasticity using IV
- Results
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**Use perfect information to calculate true elasticities**: EPEX day-ahead hourly bid curves, 2014–2015



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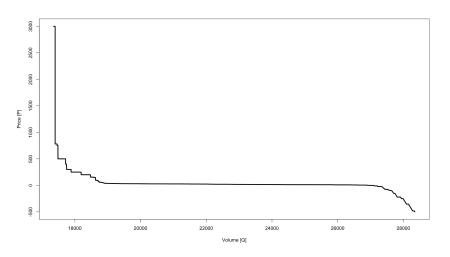


Figure: Demand bid curve for 01.05.2014, Hour 1



**Use perfect information to calculate true elasticities**: EPEX day-ahead hourly bid curves, 2014–2015

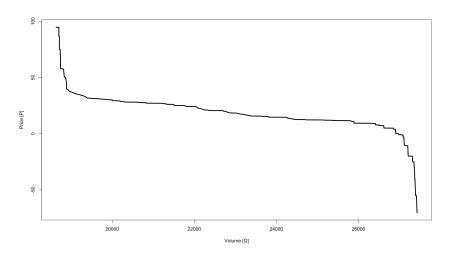


Figure: Demand bid curve for 01.05.2014, Hour 1, around equilibrium



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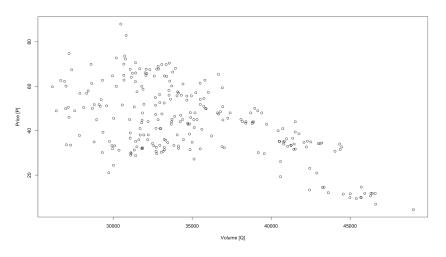


Figure: Equilibrium prices/quantities, May 2014, identification problem



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- 2 IV regression elasticities with P, Q, RES, dummies
- 3 Lasso regression combined with IV (similar to Belloni et al. [2011])



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$$\hat{\beta}_1 = \frac{1}{N} \sum_{i=1}^{N} \beta_{1,i}$$



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1st stage: Regress P on RES, wind, pv, load,  $P_{gas}$ ,  $P_{coal}$ , dummies



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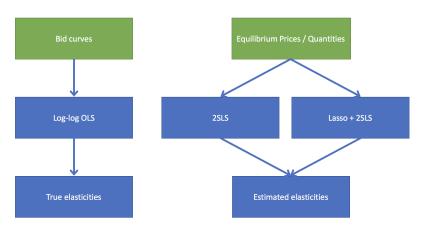
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Note: Computing standard errors of the estimation in this setting is non-trivial and requires the use of Bayesian Lasso. (*Park and Casella [2008]*).



### Overview of empirical methods





## Yearly results (Peak hours)

Model	Estimate	Std. Error	p-value
True estimate	-0.38	_	_
OLS	-0.23	0.024	<0.01
OLS, control load	-0.37	0.048	< 0.01
2SLS, RES	-0.45	0.011	< 0.01
2SLS, RES, hours	-0.37	0.012	< 0.01
2SLS, Lasso	-0.36	0.003	< 0.01
Observations	2*8760		
1st stage F-tests	1066*** / 1143***		
		•	



## Yearly results (Off-Peak hours)

Model	Estimate	Std. Error	p-value
True estimate	-0.39	_	_
OLS	-0.07	0.16	<0.01
OLS, control load	-0.13	0.031	< 0.01
2SLS, RES	-0.43	0.026	< 0.01
2SLS, RES, hours	-0.39	0.038	< 0.01
2SLS, Lasso	-0.39	0.0042	< 0.01
Observations	2*8760		
1st stage F-tests	1120*** / 1371***		
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- Locality of Instrumental Variable can yield biased resultst



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- Possibly other demand and supply shifters or a combination thereof?



Thanks for your attention!

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## Literature



J.D. Angrist and A.B. Kruger. Instrumental variables and the search for identification: From supply and demand to natural experiments. Journal of Economic Perspectives, 15:238–252, 2001.

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### **Market description**

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