Strong Exclusion for the Production Approach: Misspecification-Robust Markup Estimation

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Importance

Markups estimated from production data are now among the most heavily used objects in empirical economics. The production approach of De Loecker and Warzynski (2012) requires no demand system or conduct assumption: with an output elasticity from an estimated production function and an observed input revenue share, the markup follows from cost minimization. Its application at scale — most prominently the secular rise of market power documented by De Loecker et al. (2020) — has shaped debates in macroeconomics, industrial organization, and antitrust policy.

The same literature is also the site of one of empirical economics' sharpest methodological disputes. The elasticities on which markups load are estimated under proxy-variable assumptions (Olley and Pakes, 1996; Ackerberg et al., 2015) that are known to be approximations: a scalar Markov unobservable, deterministic timing conventions, and functional forms chosen for tractability. Bond et al. (2021) show that with revenue data the level of the markup can be severely biased; Gandhi et al. (2020) prove that gross-output elasticities are not even nonparametrically identified from standard timing assumptions; De Ridder et al. (2026) document that markup *levels* are highly sensitive to these choices while relative comparisons are far more stable; and Ackerberg and De Loecker (2024) show that imperfect competition itself contaminates the proxy inversion. Every applied user of the production approach therefore works with a model they know to be misspecified — yet the literature offers little formal guidance on *which* conclusions survive misspecification and which do not.

Andrews et al. (2025) (henceforth ABGRS) provide exactly such a framework, in general GMM settings: estimates of the causal effect of an endogenous variable remain approximately valid under local misspecification of the model's control structure essentially if and only if the moment conditions satisfy *strong exclusion* — enough instruments that are mean-independent of the included controls (their Proposition 3). Their applications are a static demand system (Miller and Weinberg, 2017) and a dynamic Cobb–Douglas production function (their App. D.3). This proposal asks what strong exclusion delivers for the workhorse empirical object built on production functions: markups, and treatment effects on markups.

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Gap

Three open questions sit between ABGRS's theory and the markup literature's practice.

(i) When do proxy-variable moments satisfy strong exclusion? The standard ACF instrument stack — lagged polynomials in inputs — is constructed *from* the controls, the classic failure mode ABGRS identify for Blundell–Bond-style internal instruments in the dynamic case (their App. B.10). External instruments that shift the productivity process, such as the lagged export or procurement status of De Loecker (2013), are the natural candidates to satisfy it. No paper characterizes conditions on the productivity process and the instrument under which proxy-variable GMM is strongly excluded, nor which of the many moment stacks used in practice come closest.

(ii) What is approximately identified: levels, or treatment effects? An empirical regularity in my own working paper motivates a conjecture. Across nine markup estimation methods and 33 specifications, estimated markup *levels* for Czech construction firms range from 1.02 to 2.17, yet the *treatment effect* of holding a procurement contract is stable at 12.5–14.3%. This is precisely the pattern ABGRS's theory predicts when the treatment-effect moments are strongly excluded while the level-defining moments are not: misspecified controls shift levels but approximately cancel in the causal contrast. Turning this from an empirical observation and a diagnostic (in my working paper, all ACF instruments pass ABGRS's partial-R^2 screen) into a theorem — conditions under which markup *differences* are approximately causally consistent even when markup *levels* are inconsistent — would rationalize a robustness pattern documented across the literature (De Ridder et al., 2026) and sharpen what applied work can and cannot claim.

(iii) How should applied researchers engineer strong exclusion? ABGRS give a general recipe — residualize instruments against controls and verify a rank condition — but no implementation exists for production functions, no diagnostic exists for the strength of the excluded component (the analogue of an effective first-stage F; cf. Montiel Olea and Pflueger, 2013), and no simulation evidence maps the boundary where the approximation fails.

Research strategy

Step 1: Theory. Cast proxy-variable estimation in ABGRS's nesting model. The researcher's model is the ACF two-step with a Markov productivity process; the nesting model allows the control function and the Markov law to be locally misspecified (non-scalar unobservables, timing violations, omitted competition terms in the sense of Ackerberg and De Loecker, 2024). Objects of interest are (a) the output elasticity, (b) the markup level, and (c) the coefficient on a firm-level treatment (procurement status) in the productivity or markup process. I will derive which moment stacks satisfy strong exclusion for each object — conjecture: external shifters à la De Loecker (2013) do for (c), lagged-input instruments do not for (a)–(b) — and prove the levels-versus-differences result of (ii) as a corollary.

Step 2: Simulation. A Monte Carlo laboratory in the spirit of ABGRS's Figure 2: data-generating processes with controlled distance from the researcher's model (translog truth vs. Cobb–Douglas estimation, AR(1) violations, correlated measurement error), comparing baseline ACF moments with strongly excluded moments. I have a working prototype: a synthetic-DGP replication of the baseline-versus-strong-exclusion bias contrast built for my ECON 5553 presentation of ABGRS, which this step scales from IV regression to the full production-function pipeline.

Step 3: Application. The Czech construction panel from my working paper (MagnusWeb financials linked to the Datlab procurement register, 2006–2021, with three transparency reforms as external variation) is a near-ideal testbed: an observed firm-level treatment, an external instrument already validated by ABGRS's own diagnostic, and 33 pre-existing specifications against which to benchmark the engineered strongly excluded estimator. Deliverables: a revised premium estimate with honest misspecification-robust confidence sets, and a practical "strong-exclusion-first" checklist for production-approach applications.

Extensions

First, a *proxy-strength diagnostic*: the weak-instrument analogue for strongly excluded components, developing the concern I raised as a referee (course referee report on NBER w34842) that faithfulness-type conditions degrade continuously as proxies weaken. Second, *dynamic games*: BBL-style two-step estimators (Bajari et al., 2007) inherit the same internal-instrument failure mode; strong exclusion may discipline which forward-simulation moments are robust, connecting to my structural procurement agenda. Third, *demand*: ABGRS note that BLP-style characteristic instruments fail strong exclusion in the static case, which motivates misspecification-robust demand estimation with external cost shifters — complementary to the nonparametric program of Compiani (2022) and Berry and Haile (2014).

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