# LEARNING CAUSAL RELATIONSHIPS FROM CONDITIONAL MOMENT RESTRICTIONS BY IMPORTANCE WEIGHTING

**Anonymous authors**
Paper under double-blind review

## ABSTRACT

We consider learning causal relationships under conditional moment restrictions. Unlike causal inference under unconditional moment restrictions, conditional moment restrictions pose serious challenges for causal inference. To address this issue, we propose a method that transforms conditional moment restrictions to unconditional moment restrictions through importance weighting using a conditional density ratio estimator. Then, using this transformation, we propose a method that successfully estimates parametric or nonparametric functions defined under conditional moment restrictions. We analyze the estimation error and provide a bound on the structural function, providing theoretical support for our proposed method. In experiments, we confirm the soundness of our proposed method.

## 1 INTRODUCTION

Consider learning the causal relationship between airline ticket prices and demand. As one might expect, prices and demand rise and fall through the seasons, being affected by other events like vacation periods, which are called confounders and may or may not be observable. Due to confounders, naively inferring from this pattern that higher (lower) prices increase (decrease) demand would be incorrect, and potentially detrimental. Thus, controlling for confounding effects is essential. This issue arises frequently in practice, especially when learning causal (structural) relationships are essential to answer counterfactual questions regarding policy intervention and outcome.

One approach to deal with confounding effects (like in the airline example above) is the instrumental variable (IV) approach. In the IV approach, the conditional moment restriction is defined as such that the causal model satisfies the restriction of zero expected value given IVs, thus conditioning out the confounding effect. The simplest representation of this idea is the two-step least squares (2SLS) for linear models. However, given the complex nature of the causal effect and confounding effect (and their relation), assuming a linear relation can be too strong. Thus, in this paper, we focus on on nonparametric IV (NPIV) regressions, allowing for much more flexible estimation.

NPIV can be viewed as an instance of a more general framework of causal inference under conditional moment restrictions. In this light, the machinery for inference under conditional moment restrictions also applies to NPIV, as well as its shortcomings. One major issue with using the conditional moment restrictions for causal inference is that one must approximate the conditional expectation, which is often difficult to do (see, e.g., Newey (1993); Donald et al. (2003); Domínguez & Lobato (2004); Otsu (2007) for parametric and Newey & Powell (2003); Ai & Chen (2003) for nonparametric IVs using sieves). For instance, Ai & Chen (2003), Lewbel (2007), and Otsu (2007) estimate the conditional expectation by local kernel density estimation. However, local kernel density estimation suffers under high dimensionality. In order to deal with this problem, Hartford et al. (2017) proposed using deep learning to estimate the localized density function, leveraging the flexibility of neural networks. While this approach conceptually succeeds, it is not easy to implement in practice due to the requirement to resample from the estimated conditional density.

In this paper, we propose transforming conditional moment restrictions into unconditional moment restrictions by importance weighting using the conditional density ratio. The conditional density ratio is defined as the ratio of the conditional probability density, conditioned on the IVs, to the unconditional probability density. We show that the unconditional expectation of a random variable

weighted by the conditional density ratio is equal to the conditional expectation. Further, we show that it is possible to estimate the conditional density ratio by using the least-squares method with a neural network. Once the conditional density ratio is estimated, the usual method of moments, such as GMM, can be used straightforwardly.

The contribution of this paper is as follows: (i) we propose a novel approach to convert conditional moment restrictions to unconditional moment restrictions by importance weighting; (ii) using our proposed transformation, we develop methods for NPIV; (iii) we analyze the estimation error, providing theoretical support for our proposed method.

## 2 SETUP AND NOTATION

Amongst various methods of learning causal relationships from conditional moment restrictions, we focus on the NPIV regression for ease of discussion. Note that our proposed method can be applied to more general settings, similar to Ai & Chen (2003).

We observe a dataset $\{(Y_i, X_i, Z_i)\}_{i=1}^n$, where $Y_i \in \mathbb{R}$ is an observable scalar random variable, $X_i \in \mathcal{X} \subseteq \mathbb{R}^{d_X}$ is a $d_X$ dimensional explanatory variable, $Z_i \in \mathcal{Z} \subseteq \mathbb{R}^{d_Z}$ is a $d_Z$ dimensional random variable, called an IV. Then, for a structural function $f^* : \mathcal{X} \to \mathbb{R}$, which represents the causal relationship between $Y_i$ and $X_i$, we define the following data-generating process:

$$Y_i = f^*(X_i) + \varepsilon_i,$$

where $\varepsilon_i$ is the sub-Gaussian error term with mean zero. To allow learning the structural function $f^*$, we suppose that we have access to the IV that satisfies the following conditional moment restrictions:

$$\mathbb{E}\left[\varepsilon_i | Z_i\right] = 0 \quad \forall i \in \{1, 2, \ldots, n\}. \tag{1}$$

Then, we also assume that under the conditional moment restriction, we can uniquely identify $f^*$. Our goal is to learn $f^*$ from the conditional moment restrictions in (1). If $Z_i = X_i$, this problem boils down to the estimation of the conditional expectation (regression function) $\mathbb{E}[Y_i|X_i]$. However, when $\mathbb{E}[\varepsilon_i|X_i] \neq 0$, $\mathbb{E}[Y_i|X_i]$ is not equivalent to $f^*(X_i)$; that is, typical regression analysis, such as least squares, may not return the correct estimate of $f^*(X_i)$.

## 3 PRELIMINARIES AND LITERATURE REVIEW

In this section, we briefly review causal inference under unconditional and conditional moment restrictions, focusing on the IV method.

### 3.1 IV METHOD FOR LINEAR STRUCTURAL FUNCTIONS

One of the basic cases of using the IV is when $f^*$ is a linear model $X_i^\top \theta^*$ with $d_X$ dimensional vector $\theta^*$ and the error term $\varepsilon_i$ is correlated with the explanatory variable $X_i$. In this case, the parameter $\theta$ of the linear model can be estimated if there are IVs of dimension $d_X$ or more that satisfies the unconditional moment restrictions, $\mathbb{E}[Z_i \varepsilon_i] = \mathbf{0}_{d_Z}$, where $\mathbf{0}_d$ is a $d$ dimensional zero vector. In the just-identified case ($d_X = d_Z$), we can estimate $\theta^*$ as $\hat{\theta}_{\mathrm{IV}} = \left(\frac{1}{n}\sum_{i=1}^n Z_i X_i^\top\right)^{-1} \frac{1}{n}\sum_{i=1}^n Z_i Y_i$. In the over-identified case ($d_X \leq d_Z$), we can estimate it by the two-stage least squares (2SLS).

In the 2SLS, we first regress $X_i$ by $Z_i$; then using a $d_X$ dimensional function $\hat{g}(Z_i)$ obtained from the first stage regression, we estimate $\theta^*$ as $\hat{\theta}_{\mathrm{2SLS}} = \left(\frac{1}{n}\sum_{i=1}^n \hat{X}_i \hat{X}_i^\top\right)^{-1} \frac{1}{n}\sum_{i=1}^n \hat{X}_i Y_i$, where $\hat{X}_{d,i} = Z_i^\top \left(\frac{1}{n}\sum_{j=1}^n Z_j Z_j^\top\right)^{-1} \frac{1}{n}\sum_{j=1}^n Z_j X_{d,j}$ and $\tilde{X}_i = (\hat{X}_{1,i}, \ldots, \hat{X}_{d_X,i})^\top$.

More generally, we can formulate the estimation of the linear structural function by unconditional moment restrictions defined using the IV; that is, $\mathbb{E}[m(\theta^*; Y_i, X_i, Z_i)] = \mathbf{0}_{d_m}$, where $\theta^* \in \Theta$ is a parameter representing the causal effect, $\Theta$ is the parameter space, and $m : \Theta \times \mathbb{R} \times \mathcal{X} \times \mathcal{Z} \to \mathbb{R}^{d_m}$ is a $d_m$ dimensional moment function. Then, the GMM estimator is defined as $\hat{\theta}_{\mathrm{GMM}} = \arg\min_{\theta \in \Theta} \left(\frac{1}{n}\sum_{i=1}^n m(\theta; Y_i, X_i, Z_i)\right)^\top W_{d_m} \left(\frac{1}{n}\sum_{i=1}^n m(\theta; Y_i, X_i, Z_i)\right)$, where $W_{d_m}$ is a $d_m \times d_m$ weight matrix. If $W_{d_m}$ is chosen as $W_{d_m}^* \propto \mathbb{E}[m(\theta^*; Y_i, X_i, Z_i)^\top m(\theta^*; Y_i, X_i, Z_i)]$,

the estimator $\hat{\theta}_{\text{GMM}}$ is efficient under the posited moment conditions. Note that the GMM includes the 2SLS as a special case where $\varepsilon_i$ has the same variance among $i \in \{1, \dots, n\}$ and the zero covariance.

Three methods have been proposed to obtain the optimal weight $W^*_{d_m}$; two-step GMM, iterative GMM, and continuous updating GMM (CU estimator; CUE). These estimators have the same asymptotic distribution, but different non-asymptotic properties. In particular, CUE is known as a special case of the generalized empirical likelihood (GEL) estimator, which plays an important role in estimation with many moment restrictions (Newey & Smith, 2004).

### 3.2 NPIV AND LEARNING FROM CONDITIONAL MOMENT RESTRICTIONS

In linear structural functions, zero covariance between the IV and error term suffices for identification. However, in nonparametric structural functions, we require a stronger restriction: the disturbance has conditional expectation zero given the IVs. Under this restriction, we can characterize the solution of NPIV as that of an integral equation $K(z) = \mathbb{E}[Y_i|Z_i = z] = \mathbb{E}[f^*(X_i)|z] = \int f^*(x)dF(x|z)$ with $F$ denoting the conditional c.d.f of $x$ given $z$. The identification problem also results in the uniqueness of the solution.

Several estimators have been proposed for this problem. Newey & Powell (2003) proposed a nonparametric analogue of the 2SLS for linear structural functions. They first define the linear-in-parameter model as a model to approximate the nonparametric structural function $f^*$, where they use a linear approximation with basis expansion, such as sieve (series) regression. Let us denote the approximation as $f^*(X_i) \approx \psi(X_i)^\top \theta^*$, where $\psi : \mathcal{X} \to \mathbb{R}^{d_\psi}$, $d_\psi \leq n$ is a vector-valued function consisting of outputs of basis functions. Then, they conduct the 2SLS as follows: (i) they define a linear-in-parameter model as an approximation to the nonparametric model of $Z_i$, and estimate $\mathbb{E}[\psi(X_i)|Z_i]$ using that model; (ii) they regress $Y_i$ by $\mathbb{E}[\psi(X_i)|Z_i]$ to estimate $\theta^*$. In contrast, Ai & Chen (2003) proposed a nonparametric analogue of the GMM. Ai & Chen (2003) also approximate the nonparametric structural function $f^*$ by a linear-in-parameter model. However, unlike Newey & Powell (2003), Ai & Chen (2003) estimate $\mathbb{E}[(Y_i - f(X_i))|Z_i]$, instead of estimating $\mathbb{E}[\psi(X_i)|Z_i]$, for a given model $f$ by another linear-in-parameter model. Using the estimator of $\mathbb{E}[(Y_i - f(X_i))|Z_i]$, Ai & Chen (2003) transform conditional moment restrictions into unconditional moment restrictions and apply the GMM to estimate $f^*$. In addition to these two typical methods, Darolles et al. (2011), Carrasco et al. (2007) have proposed their own methods for NPIV.

This is how the NPIV problem is typically cast into the framework of conditional moment restrictions, where a parameter representing the causal relationship satisfies $\mathbb{E}[m(\theta^*; Y_i, X_i, Z_i)|Z_i] = \mathbf{0}_{d_m}$. As with NPIV, we often define the moment function as a function of the nonparametric function $f$ instead of the parameter $\theta$. We can estimate parametric causal models defined under conditional moment restrictions using variants of GMM or empirical likelihood, e.g., Newey (1993); Donald et al. (2003); Ai & Chen (2003); Domínguez & Lobato (2004); Otsu (2007); Lewbel (2007), by transforming the conditional moment restrictions to unconditional moment restrictions.

### 3.3 APPROACHES IN THE MACHINE LEARNING LITERATURE

We review several approaches recently propose by the machine learning community.

**2SLS with more flexible models.** Hartford et al. (2017) extend the two-stage approach by employing a neural network density estimator, and Singh et al. (2019) does it by conditional mean embedding in RKHS, a variant of sieve regression, respectively, in the first stage. For example, in Hartford et al. (2017), they first approximate $K(z)$ by estimating $F(x|z)$ with neural networks. Then, for $B$ samples $\{\tilde{X}_j\}_{j=1}^B$ generated from the estimator $\hat{F}(x|z)$, they train a model with neural networks by minimizing the empirical risk $\frac{1}{n}\sum_{i=1}^n \left(Y_i - \frac{1}{B}\sum_{\tilde{X}_j \sim \hat{F}(X_j|Z_i)} f\left(\tilde{X}_j\right)\right)^2$.

In contrast, Xu et al. (2021) first approximate $f(X_i)$ by neural networks and regard the last layer as $\psi(X_i)$ in the 2SLS of NPIV. Then, they predict $\psi(X_i)$ by another model $\varphi(Z_i)$, approximated by neural networks. Because $\psi(X_i)$ is transitive in the learning process, they alternatively train the model $\varphi(Z_i)$ to predict $\psi(X_i)$, and the model $f(X_i)$ to predict $f^*(X_i)$.

**Minimax approach.** There has also been a recent surge in interest in minimax approaches that reformulate conditional moment restrictions as a minimax optimization problem (Bennett et al., 2019;

Bennett & Kallus, 2020; Muandet et al., 2020; Dikkala et al., 2020; Chernozhukov et al., 2020; Liao et al., 2020). For this approach, Dikkala et al. (2020) showed a strong theoretical guarantee on the estimation error bound.

# 4 PROPOSED METHOD: NPIV BY IMPORTANCE WEIGHTING

Let us define the conditional density ratio function $r : \mathbb{R} \times \mathcal{X} \times \mathcal{Z} \to \mathbb{R}$ as

$$r^*(y, x|z) = \frac{p(y, x|z)}{p(y, x)} = \frac{p(y, x, z)}{p(y, x)p(z)}.$$

Using this conditional density ratio function, we can transform conditional moment restrictions into unconditional moment restrictions as follows:

$$\mathbb{E}[(Y_i - f(X_i))|z] = \int \big(y - f(x)\big)\frac{p(y, x|z)}{p(y, x)}p(y, x)\mathrm{d}y\mathrm{d}x = \mathbb{E}\left[\big(Y_i - f(X_i)\big)r^*(Y_i, X_i|z)\right].$$

Thus, if we know the conditional density ratio function $r^*(y, x|z)$, we can approximate $\mathbb{E}[(Y_i - f(X_i))|z]$ for $z \in \mathcal{Z}$ by the following sample average:

$$\frac{1}{n}\sum_{i=1}^{n}\big(Y_i - f(X_i)\big)r^*(Y_i, X_i|z).$$

Based on this property, we propose the following two-stage method: (i) estimate the conditional density ratio function $r^*$; (ii) approximate conditional moment restrictions by the sample average of $\big(Y_i - f(X_i)\big)$ using the estimate of the conditional density ratio function $r^*$. Since we do not know the true value of the conditional density ratio $r^*$ and cannot calculate the expected value, we consider replacing $r^*$ with an estimator $\hat{r}$ and approximating the expected value with the sample mean.

## 4.1 CONDITIONAL DENSITY RATIO ESTIMATION

First, we consider estimating $r^*(y, x|z)$. While it is possible to estimate the probability density functions of the numerator and the denominator, individually, following Vapnik's principle (Vapnik, 1998), we should avoid solving more difficult intermediate problems. Sugiyama et al. (2012) summarized various methods to estimate the density ratio directly. Inspired by *least-squares importance fitting* (LSIF) of Kanamori et al. (2009), which uses the squared loss for density ratio function fitting, we estimate the conditional density ratio by minimizing the following risk:

$$\tilde{r} = \underset{r \in \tilde{\mathcal{R}}}{\arg\min}\, \frac{1}{2}\mathbb{E}_{Y,X}\left[\mathbb{E}_Z\left[\big(r^*(Y_i, X_i|Z_j) - r(Y_i, X_i|Z_j)\big)^2\right]\right],$$

where $\tilde{\mathcal{R}}$ denotes a set of measurable functions and for a function $g : \mathbb{R} \times \mathcal{X} \times \mathcal{Z} \to \mathbb{R}$, $\mathbb{E}_{Y,X}\left[\mathbb{E}_Z\left[g(Y_i, X_i, Z_j)\right]\right]$ denotes $\int g(y, x, z)p(y, x)p(z)\mathrm{d}y\mathrm{d}x\mathrm{d}z$. It is easy to confirm that $\tilde{r} = r^*$ by taking the first derivative of the risk. Because this risk includes the unknown $r^*$, it may seem intractable objective function. However, we can obtain the risk that does not include $r^*$ as

$$\begin{aligned}
&\underset{r \in \tilde{\mathcal{R}}}{\arg\min}\, \frac{1}{2}\left(\mathbb{E}_{Y,X}\left[\mathbb{E}_Z\left[r^{*2}(Y_i, X_i|Z_j) - 2r^*(Y_i, X_i|Z_j)r(Y_i, X_i|Z_j) + r^2(Y_i, X_i|Z_j)\right]\right]\right) \\
&= \underset{r \in \tilde{\mathcal{R}}}{\arg\min}\left\{-\mathbb{E}_{Y,X}\left[\mathbb{E}_Z\left[r^*(Y_i, X_i|Z_j)r(Y_i, X_i|Z_j)\right]\right] + \frac{1}{2}\mathbb{E}_{Y,X}\left[\mathbb{E}_Z\left[r^2(Y_i, X_i|Z_j)\right]\right]\right\} \\
&= \underset{r \in \tilde{\mathcal{R}}}{\arg\min}\left\{-\mathbb{E}_{Y,X,Z}\left[r(Y_i, X_i|Z_i)\right] + \frac{1}{2}\mathbb{E}_{Y,X}\left[\mathbb{E}_Z\left[r^2(Y_i, X_i|Z_j)\right]\right]\right\}.
\end{aligned}$$

Here, we used $\mathbb{E}_{Y,X}\left[\mathbb{E}_Z\left[r^*(Y_i, X_i|Z_j)r(Y_i, X_i|Z_j)\right]\right] = \mathbb{E}_{Y,X}\left[\mathbb{E}_Z\left[\frac{p(Y_i, X_i, Z_j)}{p(Y_i, X_i)p(Z_j)}r(Y_i, X_i|Z_j)\right]\right] = \mathbb{E}_{Y,X,Z}\left[r(Y_i, X_i|Z_i)\right]$. For some hypothesis class $\mathcal{R}$, by approximating the risk with its sample approximation, we estimate the conditional density ratio as

$$\hat{r} = \underset{r \in \mathcal{R}}{\arg\min}\left\{-\frac{1}{n}\sum_{i=1}^{n} r(Y_i, X_i|Z_i) + \frac{1}{2}\frac{1}{n}\sum_{j=1}^{n}\frac{1}{n}\sum_{i=1}^{n} r^2(Y_i, X_i|Z_j)\right\}.$$

For the hypothesis class $\mathcal{R}$, we can use various models, such as linear-in-parameter models and neural networks. Suzuki et al. (2008) also proposed a similar formulation based on maximum likelihood estimation with constraints, which is not easy to solve with neural networks.

### 4.2 NPIV REGRESSION BY IMPORTANCE WEIGHTING

If we know the conditional density ratio function $r^*$, we can obtain unconditional moment restrictions $\mathbb{E}_{Y,X}\left[\left(\rho(f;Y_i,X_i,Z_1,r^*)\ \rho(f;Y_i,X_i,Z_2,r^*)\ \cdots\ \rho(f;Y_i,X_i,Z_n,r^*)\right)^\top\right] = \mathbf{0}_n$, where $\rho(f;Y_i,X_i,z,r^*) = \big(Y_i - f(X_i)\big)r^*(Y_i,X_i|z)$. By replacing $r^*$ and its expectation with its estimator and the sample average, we obtain the sample vector moment restrictions, $\frac{1}{n}\sum_{i=1}^n \left(\rho(f;Y_i,X_i,Z_1,\hat{r})\ \rho(f;Y_i,X_i,Z_2,\hat{r})\ \cdots\ \rho(f;Y_i,X_i,Z_n,\hat{r})\right)^\top$.

Once we obtain the sample average, we can apply various methods for learning $f^*$ from the unconditional moment restriction. For instance, for a hypothesis class $\mathcal{F}$, we estimate $f^*$ by minimizing

$$\mathcal{R}_n(f,\hat{r}) = \frac{1}{n}\sum_{j=1}^n \left(\frac{1}{n}\sum_{i=1}^n (Y_i - f(X_i))\hat{r}(Y_i,X_i|Z_j)\right)^2. \tag{2}$$

This objective function is closely related with the risk introduced in Dikkala et al. (2020), defined as

$$\mathcal{L}(f,r^*) := \mathbb{E}_Z\left[\left(\mathbb{E}_{Y,X}\left[(f^*(X_i) - f(X_i))r^*(Y_i,X_i|Z_j)\right]\right)^2\right], \tag{3}$$

The square root of this risk is called the projected mean squared error (MSE) in Dikkala et al. (2020).

The objective function (2) is a special case of the GMM and GEL. In the GMM, we estimate $f^*$ by minimizing $\frac{1}{n}\sum_{j=1}^n \left(\frac{1}{n}\sum_{i=1}^n (Y_i - f(X_i))\hat{r}(Y_i,X_i|Z_j)\right)^\top w_j \left(\frac{1}{n}\sum_{i=1}^n (Y_i - f(X_i))\hat{r}(Y_i,X_i|Z_j)\right)$, where $w_j > 0$ is a weight (Ai & Chen, 2003). Thus, our framework of transforming conditional moment restrictions to unconditional moment restrictions using importance weighting allows us to conduct causal inference using NPIV with conditional moment restrictions using a variety of models, such as linear-in-parameter models with basis functions and neural networks.

**Linear-in-parameter models.** As an example, we introduce a linear-in-parameter model with some basis functions. Here, let us consider using the Gaussian kernel as the basis function. For $x \in \mathcal{X}$, let $\varphi(x;\sigma^2) = \left(K(x,X_1;\sigma^2),\ldots,K(x,X_n;\sigma^2)\right)^\top$, where $K(x,X_u;\sigma^2) = \exp\left(-\frac{\|x-X_u\|_2^2}{2\sigma^2}\right)$ is the Gaussian kernel with a hyperparameter $\sigma^2 > 0$ and $\|\cdot\|_2$ is the $L_2$ norm. Then, we define a linear-in-parameter model as $f(x;\sigma^2) = \beta^\top\varphi(x;\sigma^2) + \beta_0$, where $\beta \in \mathbb{R}^n$, and $\beta_0 \in \mathbb{R}$.

**Neural networks.** We can also use neural networks for approximating $f^*$. In this case, we need to carefully determine the network structures because we cannot uniquely determine the solution owing to the overparameterization. In existing studies, it is assumed that the network modes are well defined for the complexity of the nonparametric function $f^*$ and the sample size $n$.

### 4.3 LEARNING WITH OVERPARAMETRIZED MODELS

In learning from (conditional and unconditional) moment restrictions, the structural function $f^*$ is determined by the equations that the expected value of random variables satisfy. When approximating the structure function $f^*$ using a model with more parameters than the sample size, the solution cannot be uniquely determined. When minimizing the prediction error directly, such overparameterization may not pose a major problem, and, in fact, may be necessary to improve the generalization error, as a recent finding, such as Bartlett et al. (2020) in linear regression. However, in learning causal relationships from conditional moment restrictions, the objective function is the set of conditional moment restrictions. Unlike in direct prediction error minimization, a model trained to minimize empirically approximated conditional moment restrictions does not necessarily minimize the MSE for $f^*$ ($\mathbb{E}[(f(X_i) - f^*(X_i))^2]$). In fact, we empirically confirm that methods using neural network sometimes do not work well partly because of their overfitting to empirical moment minimization, not to the empirical MSE for $f^*$. Despite these potential problems, there is a strong motivation to use neural networks, owing to the reported superiority in some applications, such as computer vision and natural language processing tasks. For this reason, we introduce a heuristic to avoid this problem.

As we explained, the parameters are not uniquely determined by conditional moment restrictions alone. Therefore, from the set of parameters satisfying conditional moment restrictions, we need to

select a set of parameters that works well in prediction. We consider training a model that has the minimum MSE with $Y_i$ while satisfying conditional moment restrictions as follows:

$$\min_{f\in\mathcal{F}} \mathbb{E}\left[(Y_i - f(X_i))^2\right] \quad \text{s.t. } \mathbb{E}\left[(Y_i - f(X_i))|Z_j\right] = 0 \quad \forall j \in \{1, 2, \ldots, n\}.$$

Since it is difficult to solve constrained optimization with neural networks, we propose to solve the penalized optimization. In the case of linear combination with penalties, we train the model by

$$\min_{f\in\mathcal{F}} \frac{1}{n}\sum_{i=1}^{n}(Y_i - f(X_i))^2 + \eta \sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}(Y_i - f(X_i))\hat{r}(Y_i, X_i|Z_j)\right)^2, \tag{4}$$

where $\eta \geq 0$ is a regularization coefficient. We expect that this heuristic works well when $f^*$ is close to $\mathbb{E}[Y_i|X_i]$ even if they are different functions.

## 5 Estimation error analysis

We show the estimation error of the conditional density ratio $r^*$ and structural function $f^*$. We denote the sample counterpart of $\mathcal{L}(f, r^*)$ as

$$\mathcal{L}_n(f, r^*) = \frac{1}{n}\sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}(f^*(X_i) - f(X_i))r^*(Y_i, X_i|Z_j)\right)^2.$$

Let us denote the distributions of $(Y_i, X_i)$ and $Z_i$ by $P$ and $Q$, respectively, and define the $L^2$ risk of a function $g$ with $P$ and $Q$ as $\|g\|^2_{L^2(P\times Q)} = \int\int g^2(w)\mathrm{d}P\mathrm{d}Q$. Let us denote the distribution of $(Y_i, X_i, Z_i$ by $O$, and define the $L^2$ risk of a function $g$ with $O$ as $\|g\|^2_{L^2(O)} = \int g^2(w)\mathrm{d}O$. For ease of discussion, we put the following assumptions on the random variables.

**Assumption 1.** *The error term $\varepsilon_i$ is sub-Gaussian random variables. In addition, the distributions of $X_i$ and $Z_i$ have probability densities that are finite and bounded away from zero.*

**Assumption 2.** *The conditional density ratio $r^*(y, x|z)$ is upper bounded by a constant$0 < C < \infty$.*

Note that the randomness of $Y_i$ depends on $\varepsilon_i$ and $X_i$. Let us define the hypothesis classes of the conditional density ratio $r^*$ and structural function $f^*$ as $\mathcal{R}$ and $\mathcal{F}$, respecitively. We also suppose that the hypothesis classes are Vapnik–Chervonenkis (VC) class (for rigorous definition, see Section 2.6 in van der vaart & Wellner (1996)). This class include the true models, and the hypothesises are bounded.

**Assumption 3.** *The hypothesis class $\mathcal{R}$ is VC class, includes the true model, $r^* \in \mathcal{R}$, and all $r \in \mathcal{R}$ are uniformly bounded by $B > 0$.*

**Assumption 4.** *The hypothesis class $\mathcal{F}$ is VC class, includes the true model, $f^* \in \mathcal{F}$, and all $f \in \mathcal{R}$ are uniformly bounded by $B > 0$.*

We define a measure of complexity of the hypothesis classes: for $\mathcal{F}$, we define the complexity $\mathcal{C}_B(\mathcal{F}) := \int_0^B \sqrt{\log \mathcal{N}(\delta', \mathcal{F}, \|\cdot\|_{L^\infty})}\mathrm{d}\delta'$ with a covering number $\mathcal{N}(\delta', \mathcal{F}, \|\cdot\|) := \inf\{N|\{f_j\}_{j=1}^N \text{ s.t. } \mathcal{F} \subset \cup_{j=1}\{f|\|f - f_j\| \leq \delta'\}\}$ in terms of a sup-norm $\|f\|_{L^\infty} = \sup_x |f(x)|$.

In this following parts, for the conditional density ratio estimation, we derive the bound of the MSE $\|\hat{r} - r^*\|_{L^2(P\times Q)}$; for the structural function estimation, we derive the bound of the projected MSE $\mathcal{L}(\hat{f}, r^*)$, which corresponds to the upper bound of the MSE of $\|\hat{f} - f^*\|_{L^2(O)}$ (Section 5.3).

### 5.1 MSE of the conditional density ratio

First, we consider the MSE of the conditional density ratio. For a multilayer perception with ReLU activation function (Definition 1), we show the following bound. The proof is shown in Appendix A.2.

**Lemma 1** (MSE of $r^*$)**.** *Suppose that Assumptions 1–3 hold. Let $I(r)$ be a non-negative function on $\mathbb{R}$ and $I(r^*) < \infty$. Define $\mathcal{R}_M = \{r \in \mathcal{R} : I(r) \leq M\}$ satisfying $\mathcal{R} = \bigcup_{M\geq 1}\mathcal{R}_M$. Suppose that there exist $c_0 > 0$ and $0 < \gamma < 2$ such that $\sup_{g\in\mathcal{R}_M}\|r - r^*\| \leq c_0 M$ and $\sup_{\substack{r\in\mathcal{R}_M \\ \|r-r^*\|_{L^2(P)}\leq\delta}}\|r - r^*\|_\infty \leq c_0 M$ for all $\delta > 0$, and that $\log \mathcal{N}(\delta, \mathcal{R}_M, \|\cdot\|_{L^\infty}) = \mathcal{O}\left(M/\delta\right)^\gamma$. Then,*

$$\|\hat{r} - r^*\|_{L^2(O)} = \mathcal{O}_p\left(n^{-1/(2+\gamma)}\right) \tag{5}$$

### 5.2 PROJECTED MSE OF STRUCTURAL FUNCTION $f^*$

Next, we consider bounding the projected MSE of the structural function $f^*$. To bound the projected MSE, we use a technique associated with U-statistics. We first obtain the following lemma. Let $(Y_i, X_i)$ be $W_i$, and $W_i'$ be the i.i.d. copy of $W_i$. The proof is shown in Appendix A.3.

**Lemma 2.** *Suppose that Assumptions 1–4 hold. For any $f \in \mathcal{F}$ and $r \in \mathcal{R}$, $\mathcal{L}(f, r) = \widetilde{\mathcal{L}}(f, r) + o_p(1)$ holds as a freely chosen hyper-parameter $T \to \infty$, where*

$$\widetilde{\mathcal{L}}(f, r) = \mathbb{E}_{W,W',Z}\left[(f^*(X_i) - f(X_i))r(W_i|Z_i)(f^*(X_i') - f(X_i'))r(W_i'|Z_i)\right],$$

Regarding the form, we define an empirical version of $\widetilde{\mathcal{L}}(f, r)$ in an U-statistic form:

$$\widetilde{\mathcal{L}}_n(f, r) = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{n(n-1)}\sum_{i,i'=1, i\neq i'}^{n}(f^*(X_i) - f(X_i))r(W_i|Z_j)(f^*(X_{i'}) - f(X_{i'}))r(W_{i'}|Z_j).$$

By a property of U-statistics (for example, see Arcones & Giné (1993)), $\mathcal{L}_n(f, r) = \widetilde{\mathcal{L}}_n(f, r) + \mathcal{O}_p(1/n)$ clearly holds. Then, we can decompose the projected MSE $\mathcal{L}(\hat{f}, r^*)$ as follows:

$$\mathcal{L}(\hat{f}, r^*) = \underbrace{\widetilde{\mathcal{L}}(\hat{f}, r^*) - \widetilde{\mathcal{L}}(\hat{f}, \hat{r})}_{=:\Delta_r} + \underbrace{\widetilde{\mathcal{L}}(\hat{f}, \hat{r}) - \widetilde{\mathcal{L}}_n(\hat{f}, \hat{r})}_{=:\Delta_f} + \widetilde{\mathcal{L}}_n(\hat{f}, \hat{r}) + \mathcal{O}_p(1/n). \tag{6}$$

We can handle $\Delta_r$ by the the estimation error of $r^*$ as shown in the following lemma:

**Lemma 3.** *Suppose that Assumptions 2 holds. Then,*

$$\Delta_r = \mathcal{O}(\|\hat{r} - r^*\|_{L^2(P\times Q)}) \tag{7}$$

We evaluate the projected MSE by combining (6) with Lemma 1 and Lemma 3:

**Theorem 1.** *Assume that the conditions of Lemmas 1–2 hold. Then, for any any $\delta \in (0, 1)$, there exists a constant $c > 0$ such that the following inequality holds with $n \geq 1$ and with probability at least $1 - \delta$, for any $\gamma \in (0, 1)$:*

$$\mathcal{L}(\hat{f}, r^*) \leq c\frac{\mathcal{C}_B(\mathcal{F}) + \mathcal{C}_B(\mathcal{R})}{\sqrt{n}} + \mathcal{O}\left(\max\left\{\sqrt{\frac{\log(1/\delta)}{n}}, \frac{1}{n^{1/(2+\gamma)}}\right\}\right).$$

This result reveals the following two findings: (i) the projected MSE is affected separately by the complexity of $\mathcal{F}$ and $\mathcal{R}$, and (ii) the overall convergence is $\mathcal{O}(1/\sqrt{n})$ when these complexities are finite. For instance, when using neural networks with Definition 1, the assumptions on the hypothesis classes are satisfied (Lemma 4).

### 5.3 FROM PROJECTED MSE TO MSE OF $f^*$

Following Chen & Pouzo (2012) and Dikkala et al. (2020, Appendix C.4), we discuss the derivation of the upper bound of the MSE of $f^*$ from the projected MSE. Let us define the measure of ill-posedness of the operator $T$ with respect to the function class $\mathcal{F}$ as

$$\tau := \sup_{f\in\mathcal{R}}\frac{\|f - f^*\|_{L^2(O)}}{L(f, r^*)}.$$

Then, the MSE of $f^*$ is upper bounded as $\|f - f^*\|^2_{L^2(O)} \leq \tau^2 L(\hat{f}, r^*)$ (Chen & Pouzo, 2012; Dikkala et al., 2020). Thus, Theorem 1 also implies

$$\|\hat{f} - f^*\|^2_{L^2(O)} \leq c\tau^2\frac{\mathcal{C}_B(\mathcal{F}) + \mathcal{C}_B(\mathcal{R})}{\sqrt{n}} + O\left(\tau^2\max\left\{\sqrt{\frac{\log(1/\delta)}{n}}, \frac{1}{n^{1/(2+\gamma)}}\right\}\right).$$

Note that Dikkala et al. (2020) derived $1/n$ rate on the MSE of $f^*$. Our method cannot achieve this rate because of the convergence rate of the plug-in estimator. However, this does not mean the inferiority of the proposed method. For instance, from the computational point of view, our method is easily implemented without using minimax optimization, which is often unstable.

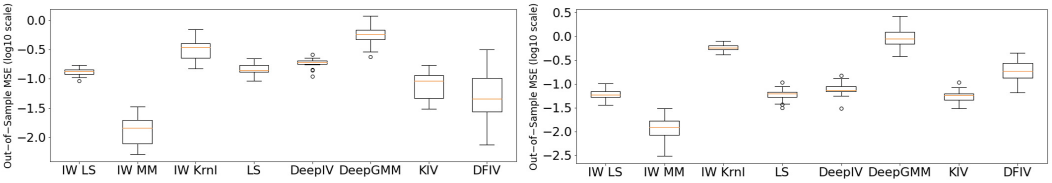


Figure 1: The log10 scaled MSEs of the setting in Newey & Powell (2003). The left graph shows the results using the original dataset. The right graph shows the results with additional IVs.

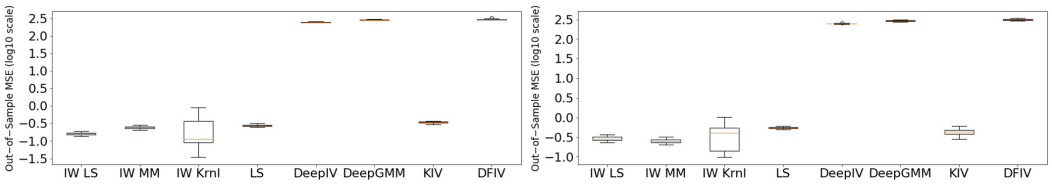


Figure 2: The log10 scaled MSEs of the original setting in Ai & Chen (2003). The left graph shows the result with $R = 0.1$ and the right graph shows the result with $R = 0.9$.

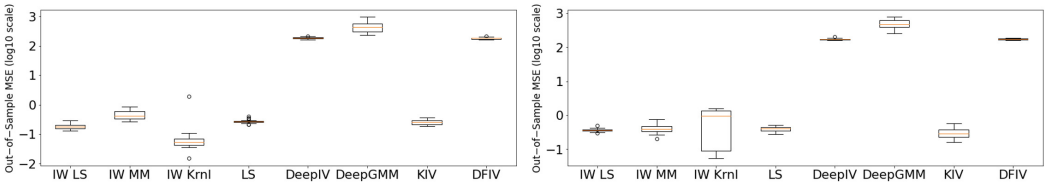


Figure 3: The log10 scaled MSEs of the setting in Ai & Chen (2003) with additional IVs. The left graph shows the result with $R = 0.1$ and the right graph shows the result with $R = 0.9$.

# 6 Experiments

We implement the following three methods based on our proposed method: first, we use neural networks to predict $f^*$ and train the model by penalized least-squares in (4) (IW-LS); second, we use neural networks to predict $f^*$ and train the model by minimizing the sum of approximated moment restrictions in (2) (IW-MM), which is the same as IW-LS except for the penalized term in the IW-LS; third, we use a linear-in-parameter model with the Gaussian kernel to predict $f^*$ and train the model by GMM (IW-Krnl). For all cases, we use neural networks for estimating $r^*$. We compare our proposed methods with four methods: DeepGMM (Bennett et al. (2019)), DFIV (Xu et al. (2021)), DeepIV (Hartford et al. (2017)), and KIV (Singh et al. (2019)). We use the datasets proposed in Newey & Powell (2003), Ai & Chen (2003), and Hartford et al. (2017). In addition, we train neural networks by simple least squares (LS), ignoring the dependency between $X_i$ and $\varepsilon_i$, as a comparison. To fairly evaluate the performances, for DeepGMM, DFIV, DeepIV, and KIV, we use the code and hyperparameters used in Xu et al. (2021)[1]. For IW-LS, IW-MM, IW-Krnl, and LS, we also follow the model and hyperparameters of the code as possible. More details are shown in Appendix B.

## 6.1 Experiments with datasets of Newey & Powell (2003) and Ai & Chen (2003)

First, we investigate the performances of the proposed methods using econometric settings of Newey & Powell (2003) and Ai & Chen (2003). These settings have simpler structures than recently proposed settings, such as in Hartford et al. (2017). When using complex and high-dimensional datasets, there is an inherent difficulty in learning due to its complexity, separate from the problem setting. Therefore, we use simple datasets to check whether the proposed method can actually learn $f^*$.

In Newey & Powell (2003), they generate $\{(Y_i, X_i, Z_i)\}_{i=1}^n$ as follows: first, they generate $\{(\varepsilon_i, U_i, Z_i)\}_{i=1}^n$ from the multivariate normal distribution $\mathcal{N}\left(\begin{pmatrix}0\\0\\0\end{pmatrix}, \left(\begin{pmatrix}1 & 0.5 & 0\\0.5 & 1 & 0\\0 & 0 & 1\end{pmatrix}\right)\right)$; then, they generate $X_i = Z_i + U_i$ and $Y_i = f^*(X_i) + \varepsilon_i$, where $f^*(X_i) = \ln(|X_i - 1| + 1)\,\mathrm{sgn}(X_i - 1)$.

[1] https://github.com/liyuan9988/DeepFeatureIV

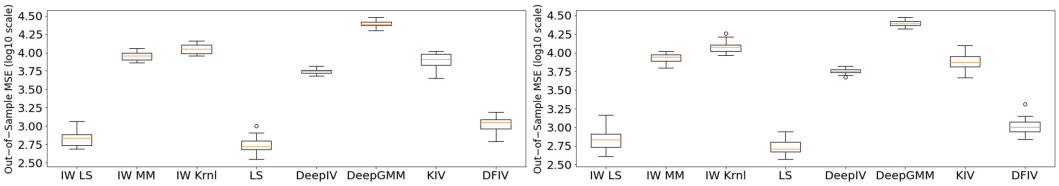


Figure 4: The log10 scaled MSEs of the demand design experiments with $1,000$ samples. The left graph show the results with $\rho = 0.25$ and the right graph shows the results with $\rho = 0.75$.

In Ai & Chen (2003), they generate $\{(Y_i, X_i, Z_i)\}_{i=1}^n$ as follows: first, they generate $\{(\varepsilon_i, X_{1i}, V_i, U_i)\}_{i=1}^n$ as $\varepsilon_i \sim \mathcal{N}\left(0, X_{1i}^2 + V_i^2\right)$, $X_{1i} \overset{\text{i.i.d.}}{\sim} \text{Unif}[0,1]$, $V_i \overset{\text{i.i.d.}}{\sim} \text{Unif}[0,1]$, and $U_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, X_{1i}^2 + V_i^2\right)$; second, they generate $X_{2i} = X_{1i} + V_i + R \times \varepsilon_i + U_i$ and $Y_1 = X_{1i}\gamma_0 + h_0\left(X_{2i}\right) + \varepsilon_i$, where $h_0\left(X_{2i}\right) = \exp\left(X_{2i}\right) / \left(1 + \exp\left(X_{2i}\right)\right)$ and $R$ is chosen as $0.9$; then, obtain $X_i = \left(X_{1i}\ X_{2i}\right)^\top$ and $Z_i = \left(X_{1i}\ V_i\right)$. Here, $\varepsilon_i$ and $U_i$ are unobservable, and $f^*(X_i) = X_{1i}\gamma_0 + h_0\left(X_{2i}\right)$, where the function $h_0$ and $\gamma_0$ are unknown.

We run each algorithm 20 times on each dataset with $n = 1,000$ and calculate the mean squared error (MSE). In the left graph of Figure 1 and Figure 2, we report the MSEs. In the dataset of Newey & Powell (2003), DFIV and our proposed IW-MM produce smaller MSE. The dataset only has a one-dimensional $X_i$, which mitigates the identification problem of neural networks. In contrast, in the dataset of Ai & Chen (2003), IW-LS leads to smaller MSE.

Because the dimensions of the IVs are low in the original settings, we add more IVs to the original settings and investigate the performances of the algorithms. The detailed settings are described in Appendix B.1. The results are shown in the right graph of Figures 1 and Figure 3.

### 6.2 Simulation studies using demand design datasets

To investigate the performance with more complicated and high-dimensional datasets, we use the demand design dataset for synthetic airline ticket sales proposed by Hartford et al. (2017). In this dataset, we observe $(Y_i, P_i, T_i, S_i, C_i)$, where $Y_i$ is sales, $P_i$ is price, $T_i$ is time, $S_i$ is consumer's emotion, and $C_i$ is cost to use as IV. Here, $T_i$ and $S_i$ are covariates, that is, $X_i = (T_i, S_i)$, and the IV is $Z_i = (C_i, T_i, S_i)$. The sales $Y_i$ is generated as $Y_i = 100 + (10 + P_i)S_i h(T_i) - 2P_i + \varepsilon_i$, where $h(t) = 2\left(\frac{(t-5)^4}{600} + \exp\left(-4(t-5)^2\right) + \frac{t}{10} - 2\right)$. Since $P_i$ is an endogenous variable and correlated with the IV, we generate $P_i$ to contain $C_i$ as $P_i = 25 + (C_i + 3)h(T_i) + V_i$. In the simulation, we assume $\varepsilon_i \sim \mathcal{N}\left(\rho V_i, 1 - \rho^2\right)$, $V_i \sim \mathcal{N}(0,1)$, $C_i \sim \mathcal{N}(0,1)$, $T_i$ is sampled from the uniform distribution with the continuous support $[0, 10]$, and $S_i$ is sampled from the uniform distribution with the discrete support $\{1, \ldots, 7\}$. Here note that $\mathbb{E}[\varepsilon_i | C_i, T_i, S_i] = \mathbb{E}[\varepsilon_i | Z_i] = 0$. The extent of correlation between $P_i$ and $V_i$ is controlled by $\rho \in \{0.25, 0.75\}$ and the larger the $\rho$ is, the more severe the correlation problem becomes.

Figure 4 shows the results with $1,000$ samples. The results under other settings are reporetd in Appendix B.2. In this setting, IW-LS and LS outperform the other methods. We consider this is because $f^*(X_i)$ takes large values compared to the error term. Under this situation, a model trained to predict $Y_i$ may perform well because the influence of $\mathbb{E}[\varepsilon_i | X_i] \neq 0$ is limited. However, the purpose of using NPIV in the first place is because the influence is large, or else effects of $\mathbb{E}[\varepsilon_i | X_i] \neq 0$ can be ignored. Therefore, this dataset is often used in the existing studies, it may not be suitable.

## 7 Conclusion

This paper proposed a method for learning causal relationships from conditional moment restrictions. Our method is based on importance weighting using the conditional density ratio, which is estimated with neural networks. The proposed method showed superior performance in experiments. We point out potential problems in recently proposed methods concerning identification and empirical performances.

## REFERENCES


Chunrong Ai and Xiaohong Chen. Efficient estimation of models with conditional moment restrictions containing unknown functions. *Econometrica*, 71(6):1795–1843, 2003. ISSN 00129682, 14680262.

Miguel A Arcones. A bernstein-type inequality for u-statistics and u-processes. *Statistics & probability letters*, 22(3):239–247, 1995.

Miguel A Arcones and Evarist Giné. Limit theorems for u-processes. *The Annals of Probability*, pp. 1494–1542, 1993.

Peter L. Bartlett, Philip M. Long, Gábor Lugosi, and Alexander Tsigler. Benign overfitting in linear regression. *Proceedings of the National Academy of Sciences*, 117(48):30063–30070, 2020. ISSN 0027-8424.

Andrew Bennett and Nathan Kallus. The variational method of moments, 2020.

Andrew Bennett, Nathan Kallus, and Tobias Schnabel. Deep generalized method of moments for instrumental variable analysis. In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

Marine Carrasco, Jean-Pierre Florens, and Eric Renault. Linear inverse problems in structural econometrics estimation based on spectral decomposition and regularization. In *Handbook of Econometrics*, volume 6B, chapter 77. Elsevier, 1 edition, 2007.

Xiaohong Chen and Demian Pouzo. Estimation of nonparametric conditional moment models with possibly nonsmooth generalized residuals. *Econometrica*, 80(1):277–321, 2012.

Victor Chernozhukov, Whitney Newey, Rahul Singh, and Vasilis Syrgkanis. Adversarial estimation of riesz representers, 2020.

S. Darolles, Y. Fan, J. P. Florens, and E. Renault. Nonparametric instrumental regression. *Econometrica*, 79(5):1541–1565, 2011. ISSN 00129682, 14680262.

Nishanth Dikkala, Greg Lewis, Lester Mackey, and Vasilis Syrgkanis. Minimax estimation of conditional moment models. In *Advances in Neural Information Processing Systems*, volume 33, pp. 12248–12262. Curran Associates, Inc., 2020.

Manuel A. Domínguez and Ignacio N. Lobato. Consistent estimation of models defined by conditional moment restrictions. *Econometrica*, 72(5):1601–1615, 2004. ISSN 00129682, 14680262.

Stephen G. Donald, Guido W. Imbens, and Whitney K. Newey. Empirical likelihood estimation and consistent tests with conditional moment restrictions. *Journal of Econometrics*, 117(1):55–93, 2003. ISSN 0304-4076.

Evarist Giné and Richard Nickl. *Mathematical foundations of infinite-dimensional statistical models*. Cambridge University Press, 2021.

Jason Hartford, Greg Lewis, Kevin Leyton-Brown, and Matt Taddy. Deep IV: A flexible approach for counterfactual prediction. In *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pp. 1414–1423. PMLR, 06–11 Aug 2017.

Wassily Hoeffding. Probability inequalities for sums of bounded random variables. *Journal of the American Statistical Association*, 58(301):13–30, 1963. ISSN 01621459.

Takafumi. Kanamori, Shohei Hido, and Masashi Sugiyama. A least-squares approach to direct importance estimation. *Journal of Machine Learning Research*, 10(Jul.):1391–1445, 2009.

Masahiro Kato and Takeshi Teshima. Non-negative bregman divergence minimization for deep direct density ratio estimation. In *Proceedings of the 38th International Conference on Machine Learning*, 2021.

Arthur Lewbel. A local generalized method of moments estimator. *Economics Letters*, 94(1):124–128, 2007. ISSN 0165-1765.

Hong Li, Chuanbao Ren, and Luoqing Li. U-processes and preference learning. *Neural computation*, 26(12):2896–2924, 2014.

Luofeng Liao, You-Lin Chen, Zhuoran Yang, Bo Dai, Mladen Kolar, and Zhaoran Wang. Provably efficient neural estimation of structural equation models: An adversarial approach. In *Advances in Neural Information Processing Systems*, volume 33, pp. 8947–8958. Curran Associates, Inc., 2020.

Krikamol Muandet, Arash Mehrjou, Si Kai Lee, and Anant Raj. Dual instrumental variable regression. In *Advances in Neural Information Processing Systems*, volume 33, pp. 2710–2721. Curran Associates, Inc., 2020.

Whitney K. Newey. 16 efficient estimation of models with conditional moment restrictions. In *Econometrics*, volume 11 of *Handbook of Statistics*, pp. 419–454. Elsevier, 1993.

Whitney K. Newey and James L. Powell. Instrumental variable estimation of nonparametric models. *Econometrica*, 71(5):1565–1578, 2003.

Whitney K. Newey and Richard J. Smith. Higher order properties of gmm and generalized empirical likelihood estimators. *Econometrica*, 72(1):219–255, 2004. ISSN 00129682, 14680262.

Taisuke Otsu. Penalized empirical likelihood estimation of semiparametric models. *Journal of Multivariate Analysis*, 98(10):1923–1954, 2007. ISSN 0047-259X.

Johannes Schmidt-Hieber. Nonparametric regression using deep neural networks with ReLU activation function. *Annals of Statistics*, 48(4):1875–1897, 2020.

Rahul Singh, Maneesh Sahani, and Arthur Gretton. Kernel instrumental variable regression. In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

Masashi Sugiyama, Taiji Suzuki, and Takafumi Kanamori. *Density Ratio Estimation in Machine Learning*. Cambridge University Press, New York, NY, USA, 1st edition, 2012.

Taiji Suzuki, Masashi Sugiyama, Jun Sese, and Takafumi Kanamori. Approximating mutual information by maximum likelihood density ratio estimation. In *Proceedings of the Workshop on New Challenges for Feature Selection in Data Mining and Knowledge Discovery at ECML/PKDD 2008*, volume 4 of *Proceedings of Machine Learning Research*, pp. 5–20. PMLR, 2008.

Sara van de Geer. *Empirical Processes in M-Estimation*, volume 6. Cambridge university press, 2000.

Aad van der vaart and Jon Wellner. *Weak Convergence and Empirical Processes: With Applications to Statistics (Springer Series in Statistics)*. Springer, 3 1996.

Vladimir N. Vapnik. *Statistical Learning Theory*. Wiley-Interscience, 1998.

Liyuan Xu, Yutian Chen, Siddarth Srinivasan, Nando de Freitas, Arnaud Doucet, and Arthur Gretton. Learning deep features in instrumental variable regression. In *International Conference on Learning Representations*, 2021.

# A PROOFS IN SECTION 5

## A.1 MATHEMATICAL TOOLS

**Concentration inequalities for empirical processes** Given a probability distribution $P$ and a random variable $g(X)$, we denote the expectation of $g(X)$ under $P$ by $\int g\mathrm{d}P$. Given samples $X_1, X_2, \ldots, X_n$ from $P$, the empirical distribution is denoted by $P_n$, and the empirical mean is denoted by $\int g\mathrm{d}P_n$; that is, $\int g\mathrm{d}P_n = \frac{1}{n}\sum_{i=1}^n g(X_i)$. We also denote $\int g\mathrm{d}P - \frac{1}{n}\sum_{i=1}^n g(X_i)$ by $\int g\mathrm{d}\big(P - P_n\big)$.

We also define

$$\rho_K^2(g) = 2K^2 \int \left(\exp\left(|g|/K - 1 - |g|/K\right)\right)\mathrm{d}P, \qquad K > 0. \tag{8}$$

Let $\mathcal{G}$ satisfy

$$\sup_{g\in\mathcal{G}} \rho_K(g) \leq R \tag{9}$$

Then, we summarize some tools used in the theoretical analysis.

**Proposition 1** (Theorem 5.11 in van de Geer (2000))**.** *$C$ is a (sufficiently large) universal constant, whereas $a$, $C_0$, and $C_1$ may be chosen, but do have to satisfy the following conditions:*

- $a \leq C_1\sqrt{n}R^2/K$;
- $a \leq 8\sqrt{n}R$;
- $a \geq C_0\left(\max\left\{\int_{a/(2^6\sqrt{n})}^R \sqrt{\log\mathcal{N}(u,\mathcal{G},\|\cdot\|)}\mathrm{d}u, R\right\}\right)$
- $C_0^2 \geq C^2(C_1+1)$.

*Then,*

$$\mathbb{P}\left(\sup_{g\in\mathcal{G}}\left|\sqrt{n}\int g\mathrm{d}\big(P_n - P\big)\right| \geq a\right) \leq C\exp\left(-\frac{a^2}{C^2(C_1+1)R^2}\right) \tag{10}$$

**Proposition 2** (Lemma 5.14 in van de Geer (2000))**.** *Let $\mathcal{G} \subset L^2(P)$ be a function class and the map $I(g)$ be a complexity measure of $g \in \mathcal{G}$, where $I$ is a non-negative function on $\mathcal{R}$ and $I(g_0) < \infty$ for a fixed $g_0 \in \mathcal{G}$. We now define $\mathcal{G}_M = \{g \in \mathcal{G} : I(g) \leq M\}$ satisfying $\mathcal{G} = \bigcup_{M\geq 1}\mathcal{G}_M$. Suppose that there exist $c_0 > 0$ and $0 < \gamma < 2$ such that*

$$\sup_{g\in\mathcal{G}_M}\|g - g_0\| \leq c_0 M, \qquad \sup_{\substack{r\in\mathcal{G}_M \\ \|g-g_0\|_{L^2(P)}\leq\delta}} \|g - g_0\|_\infty \leq c_0 M, \quad \textit{for all } \delta > 0,$$

*and that $\log\mathcal{N}(\delta,\mathcal{G}_M,P) = \mathcal{O}\left(M/\delta\right)^\gamma$. Then, we have*

$$\sup_{g\in\mathcal{G}} \frac{\left|\int(g-g_0)\mathrm{d}(P-P_n)\right|}{D(g)} = \mathcal{O}_p\left(1\right), \ (n\to\infty),$$

*where $D(g)$ is defined by*

$$D(g) = \max\left\{\frac{\|g-g_0\|_{L^2(P)}^{1-\gamma/2} I(g)^{\gamma/2}}{\sqrt{n}}, \frac{I(g)}{n^{2/(2+\gamma)}}\right\}.$$

**Lemma 4** (Lemma 9 of Kato & Teshima (2021))**.** *Let $\ell : (b_r, B_r) \to \mathbb{R}$ be a $\nu$-Lipschitz continuous function. Let $\log\mathcal{N}\left(\delta,\mathcal{F},\|\cdot\|_{L^2(P)}\right)$ denote the bracketing entropy of $\mathcal{F}$ with respect to a distribution $P$. Then, for any distribution $P$, any $\gamma > 0$, any $M \geq 1$, and any $\delta > 0$, we have*

$$\log\mathcal{N}\left(\delta,\ell\circ\mathcal{H}_M,\|\cdot\|_{L^2(P)}\right) \leq \frac{(s+1)(2\nu)^\gamma}{\gamma}\left(\frac{M}{\delta}\right)^\gamma.$$

*Moreover, there exists $c_0 > 0$ such that for any $M \geq 1$ and any distribution $P$,*

$$\sup_{\ell\circ r\in\ell\circ\mathcal{H}_M}\|\ell\circ r - \ell\circ r^*\|_{L^2(P)} \leq c_0\nu M,$$

$$\sup_{\substack{\ell\circ r\in\ell\circ\mathcal{H}_M \\ \|\ell\circ r-\ell\circ r^*\|_{L^2(P)}\leq\delta}} \|\ell\circ r - \ell\circ r^*\|_\infty \leq c_0\nu M, \quad \textit{for all } \delta > 0.$$

**Concentration inequalities for U-statistics.** Given a probability distributions $P$ and $Q$ and a random variable $g(X, Z)$, we denote the expectation of $g(X, Z)$ under $P$ and $Q$ by $\int\int g\mathrm{d}P\mathrm{d}Q$; that is, $\mathbb{E}_X\left[\mathbb{E}_Z\left[g(X,Z)\right]\right] = \int\int g\mathrm{d}P\mathrm{d}Q$. Given samples $X_1, X_2, \ldots, X_n$ from $P$ and $Z_1, Z_2, \ldots, Z_n$ from $Q$, the empirical distributions are denoted by $P_n$ and $Q_n$, and the empirical mean is denoted by $\int\int g\mathrm{d}P_n\mathrm{d}Q_n$; that is, $\int\int g\mathrm{d}P_n\mathrm{d}Q_n = \frac{1}{n}\sum_{j=1}^n \frac{1}{n}\sum_{i=1}^n g(X_i, Z_j)$. We also denote $\int\int g\mathrm{d}P\mathrm{d}Q - \frac{1}{n}\sum_{j=1}^n \frac{1}{n}\sum_{i=1}^n g(X_i, Z_j)$ by $\int\int g\mathrm{d}\big(P - P_n\big)\mathrm{d}\big(Q - Q_n\big)$.

We also define

$$\rho_K^2(g) = 2K^2 \int \left(\exp\left(|g|/K - 1 - |g|/K\right)\right)\mathrm{d}P, \qquad K > 0. \tag{11}$$

Let $\mathcal{G}$ satisfy

$$\sup_{g\in\mathcal{G}} \rho_K(g) \leq R \tag{12}$$

Then, we summarize some tools used in the theoretical analysis.

**Proposition 3** (Concentration inequality on empirical processes with U-statistics: Theorem 5 in Arcones (1995), adjusted to our setting)**.** *Suppose that $S_1, ..., S_n$ are $\mathcal{S}$-valued i.i.d. random variables and consider a class of symmetric functions $\mathcal{H} \subset L^2(\mathcal{S}\times\mathcal{S})$. Also, suppose that any function in $\mathcal{H}$ is uniformly bounded by $b > 0$ and define $\sigma^2 = \sup_{h\in\mathcal{H}} \mathrm{Var}_S(\mathbb{E}_{S'}[h(S, S')])$ where $S'$ is an i.i.d. copy of $S$. If the $\mathcal{N}(\varepsilon, \mathcal{H}, \|\cdot\|_2) \leq (A/\varepsilon)^\nu$ for some $A, \nu > 0$, for any $t \geq c$ with some $c > 0$, we obtain*

$$\begin{aligned}
&\mathbb{P}\left(n^{1/2}\sup_{h\in\mathcal{H}}\left\{\frac{1}{n(n-1)}\sum_{i,i'=1,i\neq i'}^{n} h(S_i, S_{i'}) - \mathbb{E}_{S,S'}[h(S,S)]\right\} \geq t\right) \\
&\leq 8\exp(-t^2/2^{17}(\sigma^2 + tbn^{-1/2})) + 8A^{2\nu}(\sigma^2 + 2tbn^{-1/2})^{-\nu}\exp(-n(\sigma^2 + tbn^{-1/2}/2)/2b^2) \\
&\quad + 2\exp(-t^2/(2^{11}bc(\sigma^2 + tbn^{-1/2}))).
\end{aligned}$$

**Proposition 4** (Bernsteins' inequality for U-statistics (Hoeffding, 1963; Arcones & Giné, 1993))**.** *Let $\|g\|_\infty < c$, $\int\int g\mathrm{d}P\mathrm{d}Q = 0$, and $\sigma^2 = \int\int g^2\mathrm{d}P\mathrm{d}Q$. Then, for any $a' > 0$:*

$$\mathbb{P}\left(\int\int g\mathrm{d}P_n\mathrm{d}Q_n > a'\right) \leq \exp\left(\frac{na'^2/2}{2\sigma^2 + (2/3)ca'}\right).$$

This implies that for any $a > 0$,

$$\mathbb{P}\left(\left|\int\int g - g_0\mathrm{d}\Big(P - P_n\Big)\mathrm{d}\Big(Q - Q_n\Big)\right| > \frac{a}{\sqrt{n}}\right) \leq \exp\left(\frac{a^2/2}{6\sigma^2 + 2ca/\sqrt{n}}\right).$$

As well as Suzuki et al. (2008), by applying this result, we can obtain the following result.

**Proposition 5** (From Proof of Theorem 1 in Suzuki et al. (2008))**.** *Let $\mathcal{G} \subset L^2(P\times Q)$ be a function class and the map $I(g)$ be a complexity measure of $g \in \mathcal{G}$, where $I$ is a non-negative function on $\mathcal{R}$ and $I(g_0) < \infty$ for a fixed $g_0 \in \mathcal{G}$. We now define $\mathcal{G}_M = \{g \in \mathcal{G} : I(g) \leq M\}$ satisfying $\mathcal{G} = \bigcup_{M\geq 1}\mathcal{G}_M$. Suppose that there exist $c_0 > 0$ and $0 < \gamma < 2$ such that*

$$\sup_{g\in\mathcal{G}_M}\|g - g_0\| \leq c_0 M, \qquad \sup_{\substack{r\in\mathcal{G}_M \\ \|g-g_0\|_{L^2(P\times Q)}\leq\delta}} \|g - g_0\|_\infty \leq c_0 M, \quad \textit{for all } \delta > 0,$$

*and that $\log\mathcal{N}(\delta, \mathcal{G}_M, P\times Q) = \mathcal{O}\left(M/\delta\right)^\gamma$. Then, we have*

$$\sup_{g\in\mathcal{G}}\frac{\left|\int\int(g - g_0)\mathrm{d}(P - P_n)\mathrm{d}(Q - Q_n)\right|}{D(g)} = \mathcal{O}_p\left(1\right), \ (n\to\infty),$$

*where $D(g)$ is defined by*

$$D(g) = \max\left\{\frac{\|g - g_0\|_{L^2(P\times Q)}^{1-\gamma/2} I(g)^{\gamma/2}}{\sqrt{n}}, \frac{I(g)}{n^{2/(2+\gamma)}}\right\}.$$

$$\sup_{g\in\mathcal{R}}\left|\int\int(g - g_0)\mathrm{d}(P - P_n)\mathrm{d}(Q - Q_n)\right| = \mathcal{O}_p\left(1/\sqrt{n}\right), \ (n\to\infty). \tag{13}$$

**Complexities of neural networks.**

**Definition 1** (ReLU neural networks; Schmidt-Hieber, 2020)**.** *For $L \in \mathbb{N}$ and $p = (p_0, \dots, p_{L+1}) \in \mathbb{N}^{L+2}$,*

$$\mathcal{F}(L,p) := \{f : x \mapsto W_L \sigma_{v_L} W_{L-1} \sigma_{v_{L-1}} \cdots W_1 \sigma_{v_1} W_0 x : \\ W_i \in \mathbb{R}^{p_{i+1} \times p_i}, v_i \in \mathbb{R}^{p_i} (i = 0, \dots, L)\},$$

*where $\sigma_v(y) := \sigma(y - v)$, and $\sigma(\cdot) = \max\{\cdot, 0\}$ is applied in an element-wise manner. Then, for $s \in \mathbb{N}, F \geq 0, L \in \mathbb{N}$, and $p \in \mathbb{N}^{L+2}$, define*

$$\mathcal{H}(L,p,s,F) := \{f \in \mathcal{F}(L,p) : \sum_{j=0}^{L} \|W_j\|_0 + \|v_j\|_0 \leq s, \|f\|_\infty \leq F\},$$

*where $\|\cdot\|_0$ denotes the number of non-zero entries of the matrix or the vector, and $\|\cdot\|_\infty$ denotes the supremum norm. Now, fixing $\bar{L}, \bar{p}, s \in \mathbb{N}$ as well as $F > 0$, we define*

$$\mathrm{Ind}_{\bar{L},\bar{p}} := \{(L,p) : L \in \mathbb{N}, L \leq \bar{L}, p \in [\bar{p}]^{L+2}\},$$

*and we consider the hypothesis class*

$$\bar{\mathcal{H}} := \bigcup_{(L,p) \in \mathrm{Ind}_{\bar{L},\bar{p}}} \mathcal{H}(L,p,s,F)$$
$$\mathcal{H} := \{r \in \bar{\mathcal{H}} : \mathrm{Im}(r) \subset (b_r, B_r)\}.$$

*Moreover, we define $I_1 : \mathrm{Ind}_{\bar{L},\bar{p}} \to \mathbb{R}$ and $I : \mathcal{H} \to [0, \infty)$ by*

$$I_1(L,p) := 2|\mathrm{Ind}_{\bar{L},\bar{p}}|^{\frac{1}{s+1}} (L+1) V^2,$$
$$I(r) := \max\left\{\|r\|_\infty, \min_{\substack{(L,p) \in \mathrm{Ind}_{\bar{L},\bar{p}} \\ r \in \mathcal{H}(L,p,s,F)}} I_1(L,p)\right\},$$

*where $V := \prod_{l=0}^{L+1}(p_l + 1)$, and we define*

$$\mathcal{H}_M := \{r \in \mathcal{H} : I(r) \leq M\}.$$

**Lemma 5** (Lemma 5 in Schmidt-Hieber (2020))**.** *For $L \in \mathbb{N}$ and $p \in \mathbb{N}^{L+2}$, let $V := \prod_{l=0}^{L+1}(p_l + 1)$. Then, for any $\delta > 0$,*

$$\log \mathcal{N}(\delta, \mathcal{H}(L,p,s,\infty), \|\cdot\|_\infty) \leq (s+1) \log(2\delta^{-1}(L+1)V^2).$$

**Definition 2** (Derived function class and bracketing entropy)**.** *Given a real-valued function class $\mathcal{F}$, define $\ell \circ \mathcal{F} := \{\ell \circ f : f \in \mathcal{F}\}$. By extension, we define $I : \ell \circ \mathcal{H} \to [1, \infty)$ by $I(\ell \circ r) = I(r)$ and $\ell \circ \mathcal{H}_M := \{\ell \circ r : r \in \mathcal{H}_M\}$. Note that, as a result, $\ell \circ \mathcal{H}_M$ coincides with $\{\ell \circ r \in \ell \circ \mathcal{H} : I(\ell \circ r) \leq M\}$.*

**Notations.** Let us denote a pair of random variables $(Y_i, X_i)$ by $W_i$. We denote the distribution of $(W_i, Z_i)$ by $R$ and its empirical distribution as $O_n$. Besides, we denote the distributions of $W_i$ and $Z_i$ by $P$ and $Q$, and their empirical distributions by $P_n$ and $Q_n$. For a function $g(X, Z)$, we define the $L^2$ risk over the distribution $P$ and $Q$ as

$$\|g\|_{L^2(P \times Q)} = \sqrt{\mathbb{E}_X\left[\mathbb{E}_Z\left[g^2(X,Z)\right]\right]} = \sqrt{\int\int g^2 \mathrm{d}P\mathrm{d}Q}.$$

### A.2 Proof of Lemma 1: estimation error in conditional density ratio estimation

**Lemma 6** (Decomposition of MSE)**.**

$$\|\hat{r} - r^*\|_{L^2(O)}^2 \leq \left|\mathbb{E}_{W,Z}\left[r^*(W|Z) - \hat{r}(W|Z)\right] - \frac{1}{n}\sum_{i=1}^{n}\left(r^*(W_i|Z_i) - \hat{r}(W_i|Z_i)\right)\right| \\ + \frac{1}{2}\left|\mathbb{E}_Z\left[\mathbb{E}_W\left[r^{*2}(W|Z) - \hat{r}^2(W|Z)\right]\right] - \frac{1}{n}\sum_{j=1}^{n}\frac{1}{n}\sum_{i=1}^{n}\left(r^{*2}(W_i|Z_j) - \hat{r}^2(W_i|Z_j)\right)\right|.$$

*Proof of Lemma 6.* Since The estimator $\hat{r}$ is the minimizer of the empirical risk, it satisfies the inequality

$$-\frac{1}{n}\sum_{i=1}^{n}\hat{r}(W_i|Z_i)+\frac{1}{2}\frac{1}{n}\sum_{j=1}^{n}\frac{1}{n}\sum_{i=1}^{n}\hat{r}^2(W_i|Z_j)\leq-\frac{1}{n}\sum_{i=1}^{n}r^*(W_i|Z_i)+\frac{1}{2}\frac{1}{n}\sum_{j=1}^{n}\frac{1}{n}\sum_{i=1}^{n}r^{*2}(W_i|Z_j). \tag{14}$$

Additionally, we consider an expectation of squared residuals as

$$\begin{aligned}
&\frac{1}{2}\mathbb{E}_Z\left[\mathbb{E}_W\left[\left(\hat{r}(W|Z)-r^*(W|Z)\right)^2\right]\right]\\
&=\frac{1}{2}\mathbb{E}_Z\left[\mathbb{E}_W\left[\hat{r}^2(W|Z)-2\hat{r}(W|Z)r^*(W|Z)+r^{*2}(W|Z)\right]\right]\\
&=\frac{1}{2}\mathbb{E}_Z\left[\mathbb{E}_W\left[\hat{r}^2(W|Z)\right]\right]-\mathbb{E}_{W,Z}\left[\hat{r}(W|Z)\right]+\frac{1}{2}\mathbb{E}_{W,Z}\left[r^*(W|Z)\right]\\
&\quad+\mathbb{E}_{W,Z}\left[r^*(W|Z)\right]-\mathbb{E}_{W,Z}\left[r^*(W|Z)\right]\\
&=\frac{1}{2}\mathbb{E}_Z\left[\mathbb{E}_W\left[\hat{r}^2(W|Z)\right]\right]-\mathbb{E}_{W,Z}\left[\hat{r}(W|Z)\right]-\frac{1}{2}\underbrace{\mathbb{E}_{W,Z}\left[r^*(W|Z)\right]}_{=\mathbb{E}_Z\left[\mathbb{E}_W\left[r^{*2}(W|Z)\right]\right]}+\mathbb{E}_{W,Z}\left[r^*(W|Z)\right]\\
&=-\frac{1}{2}\mathbb{E}_Z\left[\mathbb{E}_W\left[r^{*2}(W|Z)-\hat{r}^2(W|Z)\right]\right]+\mathbb{E}_{W,Z}\left[r^*(W|Z)-\hat{r}(W|Z)\right].
\end{aligned} \tag{15}$$

Taking sum of the both hand sides of (14) and (15), then we obtain the following by subtracting $-\frac{1}{n}\sum_{i=1}^{n}\hat{r}(W_i|Z_i)+\frac{1}{2}\frac{1}{n}\sum_{j=1}^{n}\frac{1}{n}\sum_{i=1}^{n}\hat{r}^2(W_i|Z_j)$ from the both side as

$$\begin{aligned}
&\frac{1}{2}\mathbb{E}_{W,Z}\left[\left(\hat{r}(W|Z)-r^*(W|Z)\right)^2\right]\\
&\leq-\frac{1}{2}\mathbb{E}_Z\left[\mathbb{E}_W\left[r^{*2}(W|Z)-\hat{r}^2(W|Z)\right]\right]+\mathbb{E}_{W,Z}\left[r^*(W|Z)-\hat{r}(W|Z)\right]\\
&\quad+\frac{1}{2}\frac{1}{n}\sum_{j=1}^{n}\frac{1}{n}\sum_{i=1}^{n}\left(r^{*2}(W_i|Z_j)-\hat{r}^2(W_i|Z_j)\right)-\frac{1}{n}\sum_{i=1}^{n}\left(r^*(W_i|Z_i)-\hat{r}(W_i|Z_i)\right).
\end{aligned}$$

Then, we obtain the statement. □

Our remaining task is to bound the following target values:

$$\sup_{r\in\mathcal{R}}\left|\mathbb{E}_Z\left[\mathbb{E}_W\left[r^2(W|Z)\right]\right]-\frac{1}{n}\sum_{j=1}^{n}\frac{1}{n}\sum_{i=1}^{n}r^2(W_i|Z_j)\right|,\text{ and} \tag{16}$$

$$\sup_{r\in\mathcal{R}}\left|\mathbb{E}_{W,Z}\left[r(W|Z)\right]-\frac{1}{n}\sum_{i=1}^{n}r(W_i|Z_i)\right|. \tag{17}$$

*Proof of Lemma 1.* Since $0<\gamma<2$, we can apply Propositions 2 and 5 in combination with Lemma 4 to obtain

$$\sup_{r\in\mathcal{H}}\frac{\left|\mathbb{E}_Z\left[\mathbb{E}_W\left[r^2(W|Z)\right]\right]-\frac{1}{n}\sum_{j=1}^{n}\frac{1}{n}\sum_{i=1}^{n}r^2(W_i|Z_j)\right|}{D_1(r)}=\mathcal{O}_p\left(1\right),$$

$$\sup_{r\in\mathcal{H}}\frac{\left|\mathbb{E}_{W,Z}\left[r(W|Z)\right]-\frac{1}{n}\sum_{i=1}^{n}r(W_i|Z_i)\right|}{D_2(r)}=\mathcal{O}_p\left(1\right),$$

where

$$D_1(r)=\max\left\{\frac{\|r^2-r^{*2}\|_{L^2(P\times Q)}^{1-\gamma/2}I(r^2)^{\gamma/2}}{\sqrt{n}},\frac{I(r^2)}{n^{2/(2+\gamma)}}\right\},\text{ and}$$

$$D_2(r)=\max\left\{\frac{\|r-r^*\|_{L^2(O)}^{1-\gamma/2}I(r)^{\gamma/2}}{\sqrt{n}},\frac{I(r)}{n^{2/(2+\gamma)}}\right\}.$$

Noting that $\sup_{r\in\mathcal{H}} I(r) < \infty$ and $\sup_{r\in\mathcal{H}} I(r^2) < \infty$. Then, for any $0 < \gamma < 2$, we have

$$\left\| \mathbb{E}_Z \left[ \mathbb{E}_W \left[ \hat{r}^2(W|Z) \right] \right] - \frac{1}{n} \sum_{j=1}^{n} \frac{1}{n} \sum_{i=1}^{n} \hat{r}^2(W_i|Z_j) \right\|_{L^2(P\times Q)}^2$$

$$\lesssim \mathcal{O}_p \left( \max \left\{ \frac{\|\hat{r}^2 - r^{*2}\|_{L^2(P\times Q)}^{1-\gamma/2}}{\sqrt{n}}, \frac{1}{n^{2/(2+\gamma)}} \right\} \right), \text{ and}$$

$$\left\| \mathbb{E}_{W,Z} \left[ \hat{r}(W|Z) \right] - \frac{1}{n} \sum_{i=1}^{n} \hat{r}(W_i|Z_i) \right\|_{L^2(P\times Q)}^2$$

$$\lesssim \mathcal{O}_p \left( \max \left\{ \frac{\|\hat{r} - r^*\|_{L^2(O)}^{1-\gamma/2}}{\sqrt{n}}, \frac{1}{n^{2/(2+\gamma)}} \right\} \right).$$

These inequalities imply

$$\|\hat{r} - r^*\|_{L^2(P\times Q)} \leq \mathcal{O}_p \left( n^{-\frac{1}{2+\gamma}} \right).$$

□

### A.3 Proof of Lemma 2

We start with the expected loss function for a learner $f : \mathcal{X} \to \mathbb{R}$ and a conditional density function $r : \mathcal{X} \times \mathcal{Y} \times \mathcal{Z} \to \mathbb{R}$ as

$$\mathcal{L}(f, r) := \mathbb{E}_Z \left[ \left( \mathbb{E}_W \left[ (f^*(X) - f(X)) r(W|Z) \right] \right)^2 \right], \tag{18}$$

where $W = (Y, X)$. For $T \in \mathbb{T}$, we consider $T$ i.i.d. random variables $W_i = (X_i, Y_i), i = 1, ..., n$ generated from a conditional distribution $P$ and approximate the inner expectation term as

$$\mathbb{E}_W \left[ (f^*(X) - f(X)) r(W|Z) \right] = n^{-1} \sum_{i=1}^{n} (f^*(X_i) - f(X_i)) r(W_i|Z) + \kappa_n(f, r),$$

where

$$\kappa_n(f, r) := \mathbb{E}_W \left[ (f^*(X) - f(X)) r(W|Z) \right] - n^{-1} \sum_{i=1}^{n} (f^*(X_i) - f(X_i)) r(W_i|Z)$$

is a residual. We substitute this form into (3) and obtain

$$\begin{aligned}
\mathcal{L}(f, r) &= \mathbb{E}_Z \left[ \left( n^{-1} \sum_{i=1}^{n} (f^*(X_i) - f(X_i)) r(W_i|Z) + \kappa_n(f, r) \right)^2 \right] \\
&= \mathbb{E}_Z \left[ n^{-2} \sum_{k,k'=1}^{T} (f^*(X_i) - f(X_i)) r(W_i|Z) (f^*(X_{i'}) - f(X_{i'})) r(W_{i'}|Z) \right] \\
&\quad + \underbrace{2\mathbb{E}_Z \left[ \kappa_n(f, r) n^{-1} \sum_{i=1}^{n} (f^*(X_i) - f(X_i)) r(W_i|Z) \right]}_{=:\mathcal{T}_1} + \underbrace{\mathbb{E}_Z [\kappa_n(f, r)^2]}_{=:\mathcal{T}_2} \\
&= \underbrace{\mathbb{E}_Z \left[ n^{-2} \sum_{i,i'=1, i'\neq i}^{n} (f^*(X_i) - f(X_i)) r(W_i|Z) (f^*(X_{i'}) - f(X_{i'})) r(W_{i'}|Z) \right]}_{=:\mathcal{T}^*} \\
&\quad + \underbrace{\mathbb{E}_Z \left[ n^{-2} \sum_{i=1}^{n} (f^*(X_i) - f(X_i))^2 r(W_i|Z)^2 \right]}_{=:\mathcal{T}_0} + \mathcal{T}_1 + \mathcal{T}_2.
\end{aligned}$$

For $\mathcal{T}_0$, the uniformly bounded property of $f^*$, $f$ and $r$ implies that it is $\mathcal{T}_0 = \mathcal{O}(1/n)$. For $\mathcal{T}_1$ and $\mathcal{T}_2$, the VC-class property and the Glivenko-Cantelli theorem (Section 2.8.1 in van der vaart & Wellner (1996)), we obtain $\kappa_n(f, r) \to 0$ in probability as $T \to \infty$ uniformly on $\mathcal{F} \times \mathcal{R}$. Associate with the boundedness of $f^*$, $f$ and $r$, we obtain that $\mathcal{T}_1 = o_p(1)$ and $\mathcal{T}_2 = o_p(1)$. About $\mathcal{T}^*$, which is an U-statistic, a convergence theorem (Theorem 3.1 in Arcones & Giné (1993)) as $n \to \infty$ implies that the U-statistic converges to $\mathbb{E}_{W,W'|Z}\left[(f^*(X) - f(X))r(W|Z)(f^*(X') - f(X'))r(W'|Z)\right]$, where $W' = (Y', X')$ is an i.i.d. copied random element of $W$. Hence, we obtain

$$\begin{aligned}\mathcal{L}(f, r) &= \mathbb{E}_Z\left[\mathbb{E}_{W,W'|Z}\left[(f^*(X) - f(X))r(W|Z)(f^*(X') - f(X'))r(W'|Z)\right]\right] + o_p(1)\\ &= \mathbb{E}_{W,W',Z}\left[(f^*(X) - f(X))r(W|Z)(f^*(X') - f(X'))r(W'|Z)\right] + o_p(1),\end{aligned}$$

for any $f \in \mathcal{F}$ and $r \in \mathcal{R}$ as $T \to \infty$.

### A.4 Proof of Lemma 3

Let us define $\xi_{\hat{f}} := \hat{f} - f^*$. We bound $\Delta_r$ by the Lipschitz continuity of $\mathcal{L}(\hat{f}, r)$ in $r$. For any $r, r' \in \mathcal{R}$, we obtain

$$\begin{aligned}\mathcal{L}(\hat{f}, r) - \mathcal{L}(\hat{f}, r') &= \mathbb{E}\left[\xi_{\hat{f}}^2(X)\xi_{\hat{f}}^2(X')(r(W|Z)r(W'|Z) - r'(W|Z)r'(W'|Z))\right]\\ &= \mathbb{E}\left[\xi_{\hat{f}}^2(X)\xi_{\hat{f}}^2(X')r(W'|Z)(r(W'|Z) - r'(W'|Z))\right]\\ &\quad + \mathbb{E}\left[\xi_{\hat{f}}^2(X)\xi_{\hat{f}}^2(X')r'(W|Z)(r(W'|Z) - r'(W'|Z))\right]\\ &\lesssim 32B'^5\|r - r'\|_{L^2(O)},\end{aligned}$$

by the Cauchy-Schwartz inequality and the uniformly bounded property over $\mathcal{F}$ and $\mathcal{R}$. As a result, if the conditional density ratio $\frac{p(w,z)}{p(w)p(z)}$ is bounded, we obtain

$$\Delta_r = \mathcal{O}(\|\hat{r} - r^*\|_{L^2(O)}^2) = \mathcal{O}(\|\hat{r} - r^*\|_{L^2(P\times Q)}^2).$$

### A.5 Proof of Theorem 1: estimation error bound

We use the following lemma to show Theorem 1.

**Lemma 7.**

$$\widetilde{\mathcal{L}}_n(\hat{f}, \hat{r}) \leq \Gamma(\hat{f}, \hat{r}) + \mathcal{O}_p\left(1/n\right).$$

*Proof.* We start with the following basis inequality following the definition of $\hat{f}$; since it is an minimizer of the empirical risk with $\hat{r}$, we obtain

$$\frac{1}{n}\sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{f}(X_i))\hat{r}(W_i|Z_j)\right)^2 \leq \frac{1}{n}\sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}(Y_i - f^*(X_i))\hat{r}(W_i|Z_j)\right)^2.$$

Since $Y_i = f^*(X_i) + \varepsilon$, the above inequality updated as

$$\frac{1}{n}\sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}(\varepsilon_i - \xi_{\hat{f}}(X_i))\hat{r}(W_i|Z_j)\right)^2 \leq \frac{1}{n}\sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}\varepsilon_i\hat{r}(W_i|Z_j)\right)^2, \tag{19}$$

where we define $\xi_{\hat{f}} := \hat{f} - f^*$. Since the left-hand side is expanded as

$$\frac{1}{n}\sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}(\varepsilon_i - \xi_{\hat{f}}(X_i))\hat{r}(W_i|Z_j)\right)^2$$
$$= \frac{1}{n}\sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}\varepsilon_i\hat{r}(W_i|Z_j)\right)^2 + \underbrace{\frac{1}{n}\sum_{j=1}^{n}\left(\frac{1}{n}\sum_{i=1}^{n}\xi_{\hat{f}}(X_i)\hat{r}(W_i|Z_j)\right)^2}_{=\mathcal{L}_n(\hat{f},\hat{r})+\mathcal{O}_p(1/n)}$$
$$\underbrace{-2\frac{1}{n}\sum_{j=1}^{n}\frac{1}{n^2}\sum_{i,i'=1,i\neq i'}^{n}\varepsilon_i\varepsilon_{i'}\xi_{\hat{f}}(X_i)\xi_{\hat{f}}(X_{i'})\hat{r}(W_i|Z_j)\hat{r}(W_{i'}|Z_j)}_{=:\Gamma(\hat{f},\hat{r})} \underbrace{-2\frac{1}{n^3}\sum_{i,j=1}^{n}\varepsilon_i^2\xi_{\hat{f}}(X_i)^2\hat{r}(W_i|Z_j)^2}_{=\mathcal{O}_p(1/n)}.$$

Substituting this expansion into (19), we obtain

$$\mathcal{L}_n(\hat{f},\hat{r}) \leq \Gamma(\hat{f},\hat{r}) + \mathcal{O}_p(1/n) \leq \sup_{f\in\mathcal{F},r\in\mathcal{R}}\Gamma(f,r) + \mathcal{O}_p(1/n).$$

Therefore,

$$\widetilde{\mathcal{L}}_n(\hat{f},\hat{r}) = \mathcal{L}_n(\hat{f},\hat{r}) + \mathcal{O}_p(1/n) = \Gamma(\hat{f},\hat{r}) + \mathcal{O}_p(1/n) \leq \sup_{f\in\mathcal{F},r\in\mathcal{R}}\Gamma(f,r) + \mathcal{O}_p(1/n).$$

□

Then we show Theorem 1.

**Step (i): Bound of $\widetilde{\mathcal{L}}_n(\hat{f},\hat{r})$.** A goal of this step is to show that the definition of $\hat{f}$ implies that for some $\epsilon \geq 0$, with high probability,

$$\widetilde{\mathcal{L}}_n(\hat{f},\hat{r}) \leq \epsilon.$$

From Lemma 7,

$$\widetilde{\mathcal{L}}_n(\hat{f},\hat{r}) \leq \Gamma(\hat{f},\hat{r}) + \mathcal{O}_p(1/n) \leq \sup_{f\in\mathcal{F},r\in\mathcal{R}}\Gamma(f,r) + \mathcal{O}_p(1/n).$$

A rest of this step is to bound $\sup_{f\in\mathcal{F},r\in\mathcal{R}}\Gamma(f,r)$. We bound the tail-probability by the Talagrand's inequality (Theorem 3.3.9 in Giné & Nickl (2021)) for U-statistics (Theorem 5 in Arcones (1995), or Theorem 1 in Li et al. (2014)) as the following inequality; for any $\delta > 0$, with probability at least $1-\delta$, we obtain

$$\sup_{f\in\mathcal{F},r\in\mathcal{R}}\Gamma(f,r) \lesssim \mathbb{E}_{\mathcal{D}}\left[\sup_{f\in\mathcal{F},r\in\mathcal{R}}\Gamma(f,r)\right] + O\left(\sqrt{\frac{\log(1/\delta)}{n}}\right),$$

provided the uniformly bounded and finite variance properties over $\mathcal{F}\times\mathcal{R}$.

To the end, we study an expectation of $\Gamma(\hat{f},\hat{r})$ in terms of the dataset $\mathcal{D} = \{(Y_i, X_i, Z_i)\}_{i=1}^n$ and obtain

$$\mathbb{E}_{\mathcal{D}}\left[\sup_{f\in\mathcal{F},r\in\mathcal{R}}\Gamma(f,r)\right] \leq \mathbb{E}_{\mathcal{D}}\left[\Gamma(f^*,r^*)\right] + \mathbb{E}\left[\sup_{f,f'\in\mathcal{F},r,f'\in\mathcal{R}}|\Gamma(f,r)-\Gamma(f',r')|\right]$$
$$\lesssim 0 + n^{-1/2}\int_0^B\sqrt{\log\mathcal{N}(\delta,\mathcal{F}\times\mathcal{R},\|\cdot\|)}d\delta.$$

Here, for the joint set $\mathcal{F}\times\mathcal{R}$, we define a distance $\|(f,r)\| := \|f\| + \|r\|$. The last inequality follows $\Gamma(f^*,r^*) = 0$ and the sub-Gaussianity inequality (Corollary 2.2.8 in van der vaart & Wellner (1996)) associated with the sub-Gaussianity of $\varepsilon_i$ and the Lipschitz continuity of $\Gamma(f,r)$ in $(f,r)$.

By these results, we obtain

$$
\begin{aligned}
&\mathcal{L}_n(\hat{f}, \hat{r}) \\
&\leq n^{-1/2} \int_0^B \sqrt{\log \mathcal{N}(\delta, \mathcal{F} \times \mathcal{R}, \|\cdot\|)} d\delta + O\left(\sqrt{\frac{\log(1/\delta)}{n}}\right) \\
&\lesssim n^{-1/2} \int_0^B \sqrt{\log \mathcal{N}(\delta', \mathcal{F}, \|\cdot\|)} d\delta' + n^{-1/2} \int_0^B \sqrt{\log \mathcal{N}(\delta', \mathcal{R}, \|\cdot\|)} d\delta' + O\left(\sqrt{\frac{\log(1/\delta)}{n}}\right),
\end{aligned}
$$

which follows $\log \mathcal{N}(\delta, \mathcal{F} \times \mathcal{R}, \|\cdot\|) \lesssim \log \mathcal{N}(\delta, \mathcal{F}, \|\cdot\|) + \log \mathcal{N}(\delta, \mathcal{R}, \|\cdot\|)$.

**Step (ii): Bound of $\Delta_f$.** To bound $\Delta_f = \widetilde{\mathcal{L}}(\hat{f}, r^*) - \widetilde{\mathcal{L}}_n(\hat{f}, r^*)$, we apply the concentration inequality on empirical processes (displayed in Proposition 3, which is originally developed in Theorem 5 in Arcones (1995)). We regard $h$ in Proposition 3 as $(y, x, y', x') \mapsto (y - f^*(x))(y' - f^*(x'))\Delta_f(x)\Delta_f(x')r(y, x|Z_j)r(y', x'|Z_j)$ and obtain

$$
\begin{aligned}
\Delta_f &= \mathbb{E}_{W,W',Z}\left[(f^*(X) - f(X))r(W|Z)(f^*(X') - f(X'))r(W'|Z)\right] \\
&\quad - \frac{1}{n}\sum_{j=1}^n \frac{1}{n(n-1)} \sum_{i,i'=1, i\neq i'}^n (f^*(X_i) - f(X_i))r(W_i|Z_j)(f^*(X_{i'}) - f(X_{i'}))r(W_{i'}|Z_j) \\
&\lesssim \sqrt{\frac{\log(1/\delta)}{n}},
\end{aligned}
$$

with probability at least $\delta$ for any $\delta \in (0, 1)$.

**Step (iii): Conclusion.** Finally, by combining the above results, with probability at least $1 - \delta$ with $\delta > 0$,

$$
\begin{aligned}
\mathcal{L}(\hat{f}, r^*) &= \underbrace{\widetilde{\mathcal{L}}(\hat{f}, r^*) - \widetilde{\mathcal{L}}_n(\hat{f}, r^*)}_{=:\Delta_f} + \underbrace{\widetilde{\mathcal{L}}_n(\hat{f}, r^*) - \widetilde{\mathcal{L}}_n(\hat{f}, \hat{r})}_{=:\Delta_r} + \widetilde{\mathcal{L}}_n(\hat{f}, \hat{r}) \\
&\leq \Delta_f + \Delta_r + n^{-1/2} \int_0^B \sqrt{\log \mathcal{N}(\delta', \mathcal{F} \times \mathcal{R}, \|\cdot\|)} d\delta' + O\left(\sqrt{\frac{\log(1/\delta)}{n}}\right) \\
&\lesssim \mathcal{O}(\|\hat{r} - r^*\|) + n^{-1/2} \int_0^B \sqrt{\log \mathcal{N}(\delta, \mathcal{F}, \|\cdot\|)} d\delta \\
&\quad + n^{-1/2} \int_0^B \sqrt{\log \mathcal{N}(\delta, \mathcal{R}, \|\cdot\|)} d\delta + O\left(\sqrt{\frac{\log(1/\delta)}{n}}\right) \\
&= n^{-1/2} \int_0^B \sqrt{\log \mathcal{N}(\delta, \mathcal{F}, \|\cdot\|)} d\delta + n^{-1/2} \int_0^B \sqrt{\log \mathcal{N}(\delta, \mathcal{R}, \|\cdot\|)} d\delta \\
&\quad + O\left(\max\left\{\sqrt{\frac{\log(1/\delta)}{n}}, \frac{1}{n^{1/(2+\gamma)}}\right\}\right) \quad \text{(from Lemma 1).}
\end{aligned}
$$

# B Experimental settings and additional results

## B.1 Simulation studies using economics datasets

Here, we report the details of the model and hyperparameters used in our experiments. Since the network structures used in Ai & Chen (2003) and Newey & Powell (2003) have many common features, we describe the network structure in Newey & Powell (2003).

For DeepGMM, DFIV, DeepIV, and KIV, we use the same model and hyperparameters published by Xu et al. (2021). For IW-LS, we use the following two networks for estimating density ratio and predicting $f^*$ respectively : FC(4,128)-FC(128,128)-FC(128,1) and FC(1,128)-FC(128,128)-FC(128,1). Each fully-connected layer (FC) is followed by leaky ReLU activations with leakiness

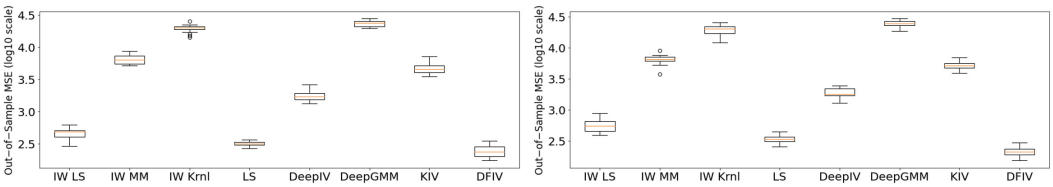


Figure 5: Demand design experiments with $5,000$ samples. The left graph show the results with $\rho = 0.25$ and the right graph shows the results with $\rho = 0.75$.

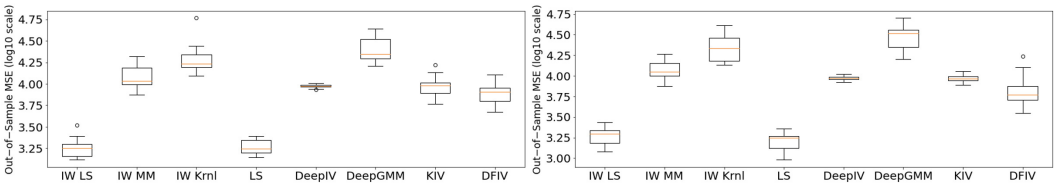


Figure 6: Demand design experiments with stronger correlation between $X_i$ and $\varepsilon_i$. The sample sizes are $1,000$. The left graph show the results with $\rho = 0.25$ and the right graph shows the results with $\rho = 0.75$.

$\alpha = 0.2$. A regularization coefficient $\eta$ is set to 0.001 as a result of cross-validation. For LS, we use the same network structure in IW-LS for predicting $f^*$. For IW-MM, we use the same network structure as IW-LS. For IW-Krnl, the same network structure as IW-LS to estimate the density ratio and $\zeta$ and $\sigma^2$ are selected via cross-validation. In Ai & Chen (2003) experiment, we change only the first layer in the network structure to match the dimension of $X_i$, and the rest of the network structure is the same.

In addition to the original settings of Newey & Powell (2003) and Ai & Chen (2003), we investigate cases where we add more IVs. In Newey & Powell (2003), we generate $\{(Y_i, X_i, Z_i, W_{i,1}, W_{i,2}, W_{i,3})\}_{i=1}^n$, where $W_{i,1}, W_{i,2}, W_{i,3}$ are additional IVs, as follows: first, they generate $\{(\varepsilon_i, U_i, Z_i, W_{i,1}, W_{i,2}, W_{i,3})\}_{i=1}^n$ from the multivariate normal distribution $\mathcal{N}\left(\begin{pmatrix}0\\0\\0\\0\\0\\0\end{pmatrix}, \begin{pmatrix}1 & 0.5 & 0 & 0 & 0 & 0\\ 0.5 & 1 & 0 & 0 & 0 & 0\\ 0 & 0 & 1 & 0 & 0 & 0\\ 0 & 0 & 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 0 & 0 & 1\end{pmatrix}\right)$; then, they generate $X_i = Z_i + \sum_{j=1}^3 W_{i,j} + U_i$ and $Y_i = f^*(X_i) + \varepsilon_i$, where $f^*(X_i) = \ln(|X_i - 1| + 1)\,\mathrm{sgn}(X_i - 1)$. Here, $\varepsilon_i$ and $U_i$ are unobservable. In Ai & Chen (2003), they generate $\{(Y_i, X_i, Z_i, W_{i,1}, W_{i,2}, W_{i,3})\}_{i=1}^n$, where $W_{i,1}, W_{i,2}, W_{i,3}$ are additional IVs, as follows: first, they generate $\{(\varepsilon_i, X_{1i}, V_i, U_i)\}_{i=1}^n$ as $\varepsilon_i \sim \mathcal{N}\left(0, X_{1i}^2 + V_i^2\right)$, $X_{1i} \overset{\text{i.i.d.}}{\sim} \text{Unif}[0,1]$, $V_i \overset{\text{i.i.d.}}{\sim} \text{Unif}[0,1]$, $\begin{pmatrix}W_{i,1}\\W_{i,2}\\W_{i,3}\end{pmatrix} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(\begin{pmatrix}0\\0\\0\end{pmatrix}, \begin{pmatrix}1 & 0.3 & 0.3\\ 0.3 & 1 & 0.3\\ 0.3 & 0.3 & 1\end{pmatrix}\right)$, $W_i = \sum_{j=1}^3 W_{i,j}$, and $U_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, X_{1i}^2 + V_i^2 + |W_i|\right)$; second, they generate $X_{2i} = X_{1i} + V_i + W_i + R \times \varepsilon_i + U_i$ and $Y_1 = X_{1i}\gamma_0 + h_0\left(X_{2i}\right) + \varepsilon_i$, where $h_0\left(X_{2i}\right) = \exp\left(X_{2i}\right) / \left(1 + \exp\left(X_{2i}\right)\right)$ and $R$ is chosen as 0.9; then, obtain $X_i = \left(X_{1i}\ X_{2i}\right)^\top$ and $Z_i = \left(X_{1i}\ V_i\ W_{i,1}\ W_{i,2}\ W_{i,3}\right)$. Here, $\varepsilon_i$ and $U_i$ are unobservable, and $f^*(X_i) = X_{1i}\gamma_0 + h_0\left(X_{2i}\right)$, where the function $h_0$ and $\gamma_0$ are unknown.

### B.2 Simulation studies using demand design datasets

For DeepGMM, DFIV, DeepIV, and KIV, we use the exact same model and hyperparameters in Xu et al. (2021). For LS and IW-LS, we use the network structure based on the economics datasets network. $\eta$ is 0.001 as a result of cross-validation. For IW-Krnl, we use the same network structure as IW-LS to estimate the density ratio and select $\zeta$ and $\sigma^2$ via cross-validation.

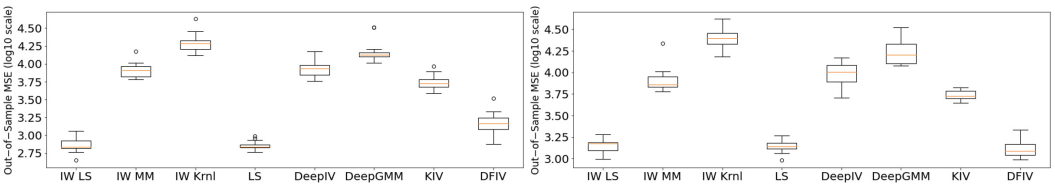


Figure 7: Demand design experiments with stronger correlation between $X_i$ and $\varepsilon_i$. The sample sizes are $5,000$. The left graph show the results with $\rho = 0.25$ and the right graph shows the results with $\rho = 0.75$.

Figure 5 shows the results with $5000$ samples. First, our proposed IW-LS outperforms the existing methods and minimizes the MSE. Second, LS, which is a naive nonlinear regression without IV, outperforms the other existing methods using IV. In contrast, IW-LS outperforms LS.

We consider the case where endogeneity causes a larger change in outcome. Since the original demand design dataset has a small effect of the bias, we slightly change $V_i$ in the price equation: $P_i = 25 + (C_i + 3)h(T_i) + 10V_i$. In the original dataset, $Y_i$ is generated as $Y_i = 100 + (10 + P_i)S_i h(T_i) - 2P_i + \varepsilon_i$. However, because the impact of $\varepsilon_i$ on the price is very limited because the variance of $\varepsilon_i$ is relatively small compared with that of $Y_i$. This is the reason why the LS also performs well in the previous result, that is, we can obtain good performance even when ignoring the endogeneity (because $f^*(X_i)$) is close to $\mathbb{E}[Y_i|X_i]$). For this reason, this dataset is not appropriate for investing the performances of the methods, although it is used in existing studies. Here, we consider the different model $Y_i = 100 + (10 + P_i)S_i h(T_i) - 2P_i + 100\varepsilon_i$, in which we multiply the error term by $100$. In this case, the bias has a more serious impact on the values of price and outcome. Figure 6 shows the results with $1,000$ samples, and Figure 6 shows the results with $5,000$ samples. Regardless of the sample size and $\rho$, our proposed method outperforms existing methods. Even in this experiment, the LS still performs well. We consider that this is because the correlation between $X_i$ and $\varepsilon_i$ is not strong. In the dataset, $V_i$, which is a cause of the bias, follows a standard normal distribution and has a limited impact on price due to the constant term $25$ ($P_i = 25 + (C_i + 3)h(T_i) + V_i$), that is, in the variation of $P_i$, $V_i$ has a small effect compared with the other variables.

In this dataset, $f^*(X_i)$ takes large values compared to the error term. Under this situation, a model trained to predict $Y_i$ may perform well because the influence of $\mathbb{E}[\varepsilon_i|X_i] \neq 0$ is limited. However, the purpose of using NPIV in the first place is because the latter influence is large, or else effects of $\mathbb{E}[\varepsilon_i|X_i] \neq 0$ can be ignored. As expected, in our experiments using Hartford et al. (2017), the least-squares method also performs well, even though the training process ignores the problem of NPIV. To investigate the performance for causal inference, we recommend using simpler datasets, before using more complicated datasets.