Causal Inference References

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We have used these references in our own research and found them very valuable. We will update citations periodically and create other ways to access this information in the future.

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