We thank the reviewers for spending their time and providing such a favorable assessment and helpful feedback. We will try to incorporate the suggestions into our manuscript. Below, we address the main issues raised by the reviewers.

Reviewer 1:

- Background material: Our aim was to make the paper as self-contained as possible, however, we do agree that it would be desirable to have more space to expound the new results. There is a non-trivial trade-off but we will try to shorten the background material and provide further elaboration and examples for the new results.
- Related work: We described the state of the art in the introduction. The problem of identifying conditional causal effects given a fully specified causal diagram has been solved by [Tian, 2004; Shpitser and Pearl, 2006], which presented complete algorithms. In this paper, we are dealing with the problem of conditional causal identification given an equivalence class of causal diagrams represented by a PAG, rather than a single causal diagram. This problem setting is more realistic, but it's also significantly more challenging, which we suspect is one of the reasons relatively fewer results are available in the literature. Among the attempts to solve this problem are [Zhang, 2007] and [Jaber et al., 2019], but each had its shortcomings as discussed in the introduction (lines 45-53) and Section 4 (lines 168-176), which indeed motivated this work.
- "The $do(X = x)$ operation require replacing the value x for X but also removing all incoming influences on node X.": Your observation is correct. Note that "replacing the original equation for X by the constant x" does eliminate all incoming influence on X as we are modifying the pre-interventional (natural) structural function underlying X (or f_x), and not just conditioning on the constant value x.
- Definite c-component: Throughout the paper, we use the abbreviation "dc-component" for "definite c-component", which is defined on pg. 4, lines 132-133. We will make this clearer and double check other such terms.

Reviewer 2:

- Set $\mathbf{U}$ in SCM definition: We apologize for the confusion. Actually variables in $\mathbf{U}$ can only be parents of variables in $\mathbf{V}$. For the purposes of this paper, it is helpful to distinguish between observed parents of a variable V_i, which are denoted as $\mathbf{Pa}_i$ (and is a subset of $\mathbf{V}$), and unobserved parents of V_i, which are denoted as $\mathbf{U}_i$ (and is a subset of $\mathbf{U}$).
- Small $\mathbf{pa}_i$: This is indeed a specific value assignment to the variables set $\mathbf{Pa}_i$.
- Formula 1: To illustrate the formula, consider an SCM where $\mathbf{V} = \{V_1, V_2\}$, $\mathbf{U} = \{U\}$, $\mathbf{F} = \{V_1 \leftarrow f_1(U), V_2 \leftarrow f_2(V_1, U)\}$, and $P(U)$. Thus, we have $\mathbf{Pa}_1 = \emptyset$, $\mathbf{Pa}_2 = \{V_1\}$, $\mathbf{U}_1 = \{U\}$, and $\mathbf{U}_2 = \{U\}$. The corresponding causal diagram is $G = \{V_1 \rightarrow V_2, V_1 \leftrightarrow V_2\}$, where $V_1 \leftrightarrow V_2$ represents the unmeasured common cause/parent U of V_1 and V_2. Any distribution generated by the above model factorizes as follows:

  $$P(V_1, V_2, U) = P(V_1|U)P(V_2|V_1, U)P(U)$$

  Recall that U is an unmeasured variable, thus what we can sample from is the marginal distribution over $\{V_1, V_2\}$ which can be written as follows.

  $$P(\mathbf{V}) = \sum_u P(V_1, V_2, u) = \sum_u P(V_1|u)P(V_2|V_1, u)P(u)$$

  The formula can be written with lower case letters standing for the value assignments of the variables, which leads to a formula akin to the one in the paper.
- Clarity/more examples: We will add more examples in the paper to improve the readability and clarity.
- Code: We certainly agree with your suggestion and plan to make the code of our work available, which we expect can lead to a smoother connection between the theory and its practical use. We appreciate your suggestion.

Reviewer 3:

- Completeness: We share the "feeling" of the reviewer regarding the completeness proof, but we do not yet have it yet. Having said that, we also would like to share that we strongly believe the conjecture is true and we are working hard towards establishing this statement more formally.
- Clarity: We tried to make the paper as self-contained as possible within the page limit, but we understand that a more thorough discussion would be more readable for the wider audience. We will do our best to improve the clarity of the paper for beginners in causal inference. Also, since the focus of the paper is more on the identifiability part, and not yet on estimation from finite samples, we didn't include numerical examples/empirical results. Still, we plan to try to account for this challenge in the near future.