Estimating dynamic treatment effects is essential across various disciplines, offering nuanced insights into the time-dependent causal impact of interventions. However, this estimation presents challenges due to the "curse of dimensionality" and time-varying confounding, which can lead to biased estimates. Additionally, correctly specifying the growing number of treatment assignments and outcome models with multiple exposures seems overly complex. Given these challenges, the concept of doublerobustness, where model misspecification is permitted, is extremely valuable, yet unachieved in practical applications. This paper introduces a new approach by proposing novel, robust estimators for both treatment assignments and outcome models. We present a "sequential model double robust" solution, demonstrating that double robustness over multiple time points can be achieved when each time exposure is doubly robust. This approach improves the robustness and reliability of dynamic treatment effects estimation, addressing a significant gap in this field.