THE HIDDEN ECONOMIC COST OF GENDER

How Income and Labour Shape Family Priorities

Evidence from U.S Household Data

Fall 2024

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Causal Effects of Hours and Income on U.S. Family Expenditures: A Double Machine Learning Evaluation

January 24, 2025

Abstract

This study examines the causal effects of hours worked and income differences between genders on family expenditures in the United States. Utilizing data from the Panel Study of Income Dynamics post-1998, we employ a two-way fixed effects regression model and a Double Machine Learning approach to mitigate biases and control for unobserved confounders. Our analysis focuses on how intra-household gender dynamics, particularly differences in income and labor contributions between men and women, influence household spending on non-essential items such as education and healthcare. Our findings reveal that while income disparities do not significantly affect family expenditure patterns due to advanced economic structures like credit access and social safety nets, differences in labor hours play a critical role in shaping spending priorities, highlighting the influence of time-use dynamics on household decision-making. This research contributes to understanding the nuanced role of gender in economic behaviors and offers implications for policies aimed at enhancing work-life balance and reducing gender inequalities in the labor market.

1 Executive Summary

This paper investigates the impact of intra-household gender dynamics on family expenditure patterns in the United States, focusing on how differences in income and labour contributions between men and women influence spending priorities. Household resource allocation has long been shaped by gendered norms, with evidence suggesting that men and women prioritize expenditures differently. Women often emphasize immediate family needs, such as childcare, education, and healthcare, while men are more inclined toward investments and personal expenditures. This study extends previous research by applying econometric and machine learning methods to understand these dynamics in the United States, where resource availability and societal norms differ significantly from those in developing countries. The primary objective is to determine how changes in women's economic participation—measured through income and labour disparities—affect household spending on family-related priorities. To achieve this, the study uses a two-way fixed effects regression model to control for time-invariant state-specific factors and nationwide economic shocks. Additionally, a Double Machine Learning approach is employed to address the limitations of traditional methods, such as potential biases from unobserved confounders.

The analysis is based on data from the Panel Study of Income Dynamics, restricted to the period after 1998 to ensure consistency in variable definitions. The primary dependent variable represents the share of household income allocated to non-essential family-related spending, such as education and healthcare. Two key explanatory variables are used: the difference in hours worked (Diff_Hours) and the difference in income earned (Diff_Income) between men and women in the household. These variables act as proxies for bargaining power and economic contributions. We find no significant relationship between income disparities and family expenditure patterns in the U.S. context. This suggests that households in developed economies may have mechanisms that mitigate the effects of income inequalities, such as credit access or social safety nets. These findings contrast with those from developing countries, where income gaps often have a more pronounced impact on resource allocation. On the other hand, differences in hours worked emerge as a significant determinant of family expenditure patterns in models that include comprehensive financial and employment controls. Households where one partner works significantly more hours often adjust spending priorities. This potentially reflects shifts in bargaining power or the need to compensate for reduced time availability.

These findings emphasize the importance of time-use dynamics in shaping household decision-making. Policies aimed at promoting work-life balance, such as flexible work arrangements or affordable childcare, could alleviate the pressures of unequal labor contributions and improve family well-being. Additionally, while income disparities may not directly affect spending patterns in high-income contexts, addressing structural gender inequalities in the labor market remains important. This research sheds light on how gender dynamics and labour contributions shape household spending. This can offer valuable insights for economists and policymakers working to create fairer and more effective strategies for resource allocation and economic growth.

2 Introduction

The allocation of household resources has an established history of being influenced by gender-based dynamics within households. Differences in spending priorities across men and women – often stemming from cultural norms – may result in differing family and business outcomes. Previous research has demonstrated this difference in household expenditure priorities, with women typically focusing the bulk of their spending on immediate family needs, such as childcare, education, and food (Senauer et al., 1988). This may align with the nurturing roles traditionally assigned to women in many societies. In contrast to this, men tend to allocate resources towards productive assets and personal expenditures. These may include expenditure on tools, equipment, or other means intended to improve their earning capacity. This allocation may align more with societal expectations of men to be providers, which prioritizes securing steady future income and/or demonstrating economic success.

2.1 Motivation

The contrast in spending patterns across genders may have wider implications. When women control household expenditures, there is evidence to suggest that families experience improved outcomes in areas such as nutrition, education, and overall well-being. In contrast, male-driven expenditure patterns, while potentially improving long-term earnings, may not prioritize immediate family needs to the same extent. Understanding how changes in income distributions within households impacts family expenditure may be of interest to a number of groups. This question can provide insights into gender dynamics and potentially enable governments to enact policies that can bring about larger increases in productivity growth. For instance, if child development is a more important concern than individual earnings growth, governments can implement fiscal policies designed to increase the share of income brought in by women. Policymakers can promote equitable economic outcomes within households through targeted tax benefits or welfare programs, aimed at supporting family spending. In a similar vein, this information would prove valuable to development economists seeking to identify strategies for economic empowerment.

2.2 Our Approach

This paper uses Consumption Data from the United States to analyze the impact of gendered income and labor dynamics on household expenditure patterns. By focusing on spending patterns across key family-related categories such as childcare, education, and healthcare, we aim to uncover how shifts in gender roles and contributions to household income shape decision-making. To identify causal relationships, we employ a two-way fixed effects regression framework. This model allows us to control for unobserved, time-invariant characteristics at the state level, such as cultural norms or economic conditions, as well as year-specific shocks that may simultaneously influence all households, such as nationwide economic recessions or policy changes. By controlling for these fixed effects, we ensure that our results reflect within-state, over-time variations in household spending rather than cross-sectional or temporal confounders.

Key explanatory variables in our analysis include measures of income and labor disparities between genders, which serve as proxies for bargaining power within households. These variables are complemented by a number of control variables to account for demographic, employment, and financial factors that may independently affect expenditure decisions. Through successive model specifications, ranging from baseline regressions to those incorporating comprehensive controls, we isolate the contributions of gender dynamics to family spending patterns. A detailed description of control variables can be found in the Appendix.

In addition to the two-way fixed effects framework, we employ a Double Machine Learning (DML) model to estimate the relationship between gendered household dynamics and family expenditures. The DML approach is particularly suited for dealing with confounding variables and ensures robust findings by combining machine learning methods with traditional econometric approaches. Structured similarly to our fixed effects model, the DML framework utilizes a random forest algorithm to estimate nuisance parameters such as control variable effects, while preserving the interpretability of our main variables of interest. This allows us to account for complex interactions and non-linearities in demographic, financial, and employment characteristics without introducing bias into our estimates of the key relationships. The use of this method serves as an alternative approach to measure against our linear model.

3 Literature Review

A number of papers have examined the issue of differences in spending priorities across genders. Senauer et al. (1988) studied food distribution across family members in rural areas in the Philippines. They estimated that a higher wage rate for women (wives/mothers) resulted in positive impacts on their own caloric intake, as well as their children's (Senauer et al., 1988). This suggests that greater economic power for women is correlated with improved family nutrition. Conversely, they found that higher male wages were correlated with increased calorie allocations for themselves and their wives, but reduced allocations for the children. The study also found a consistent gender bias favouring boys in calorie allocation (Senauer et al., 1988). Notably, they observed a significant negative link between the male's education and their caloric allocation, potentially indicating increases in altruism with education.

Additionally, Thomas (1994) studies the allocation of parental resources and its impact on child health in households across the United States, Brazil, and Ghana. The study finds that women allocate resources more significantly toward their daughters' health, while men favor their sons (Thomas, 1994). Maternal education and non-labor income are found to have significant, positive impacts on daughters' health. Fathers' education and income, on the other hand, have larger impacts on sons (Thomas, 1994). These differences suggest that women prioritize immediate family needs, particularly for daughters, while men tend to align their resource allocation with traditional gender roles, favoring investments in sons. While the paper examines data for the U.S., it does not focus on identifying overall expenditure priorities but rather explores how resource allocation varies based on the gender of the child.

Deschênes et al. (2020) further examine gendered spending responsibilities and priorities within households in Sub-Saharan Africa and South Asia, highlighting distinct expenditure patterns. They find that Women often prioritize daily household needs, focusing on family well-being through spending on food and children's education (Deschênes et al., 2020). This aligns with their culturally assigned roles as caregivers. Men, conversely, manage infrequent but substantial expenses, such as housing, education, and healthcare, and tend to allocate resources towards investments or activities aimed at enhancing their social standing or long-term income stability (Deschênes et al., 2020).

Haushofer and Shapiro (2016), on the other hand, found that spending differences were not consistently significant among female recipients compared to males. While women recipients still showed a tendency to allocate more to food and household essentials, statistical power limitations may have obscured more nuanced effects. Similarly, Kenayathulla (2015) studies differences in educational outcomes across families in Malaysia, an upper-middle-income country. They do not find significant gender gaps for boys and girls at the national level, potentially demonstrating that this phenomenon reduces with economic development.

3.1 Contribution to Existing Literature

The majority of previous literature has focused on identifying the existence of these spending inconsistencies in developing countries, where societal roles and norms may have a larger role to play. While it is possible that the issue is persistent only in developing regions, the lack of analysis of consumption patterns in developed nations represents a research gap. Although large strides have been taken in these countries towards gender equality, its full attainment is still a goal to be achieved. Thus, it is a distinct possibility that developed nations have similar gender discrepancies, although likely to a lesser extent. Our paper focuses on consumption data from the United States – in particular, beginning from 1998. Feminist movements were widespread at this point, with a larger proportion of the female population participating in the workforce. Hence, our goal is to identify if spending patterns continue to have differences across gender in developed nations, and in the modern era.

In addition to the time frame of our dataset, no previous research (to the best of our knowledge) has employed a machine learning algorithm for causal inference to study this topic. This novel approach sets our study apart and contributes a unique perspective to the existing body of literature. Specifically, our study employs Double Machine Learning, which enables us to flexibly account for high-dimensional covariates while maintaining the robustness required for causal inference. Double Machine Learning mitigates the bias often introduced by regularization in traditional machine learning methods by using a cross-fitting procedure. This method improves our ability to isolate the average treatment effect of key variables such as working hours and income on consumption, accounting for a wide array of covariates including demographic, employment, and financial factors.

4 Data and Variables

4.1 Data Sources

Our analysis utilises a dataset from a paper by Attanasio and Pistaferri (2014). The original paper analyzed trends in consumption inequality in the United States, arguing that consumption inequality more closely tracks with income inequality than previously thought. The data collected for their paper was taken from the Panel Study of Income Dynamics, a longitudinal household survey which has gathered data on households since 1968. For our analysis, we restricted the data to begin in 1998, since some of the variables of interest did not have observations prior to this year.

4.2 Key Variables of Interest

Our primary goal is to determine the impact of increases in the difference of earnings and hours worked between men and women on family expenses. Since the original dataset did not have any single, clear variable that would function as a proxy for expenses on family, we constructed the following variable:

$$FamilyExpense = childcare + tuition + otherschool + totalhealth$$

Here, the variable *FamilyExpense* is defined to be the sum of expenses on childcare, tuition, other school expenses, and total healthcare expenditure for the household. While spending on food, housing and, clothing are essential goods, we believe that the variables used in *FamilyExpense* are considered less essential by most households. Thus, a higher value of *FamilyExpense* may indicate higher priorities given to family expenses beyond the essential.

However, it is important to recognize that this variable – in absolute terms – may not be indicative of true priorities for a household. Richer households have more income available to spend, and so would be more likely to spend more on all forms of consumption. This would mean that the variable *FamilyExpense* is not a true representation of household priorities. As a result, we define:

$$PropFExpense = FamilyExpense/y,$$

where y is a variable representing total household income. Thus, *PropFExpense* represents the proportion of household income allocated to non-essential family expenditure, and functions as our **dependent variable** in the models specified in this paper. This would be more representative of household priorities, though it still may be biased due to diminishing returns to investment in these variables – for instance, richer households would only invest up to a point in a child's education, after which there are no additional returns. For our independent variables, we define two treatment variables:

$$Diff\_Hours = hours - hourw$$

Here, *hours* represents the annual number of hours worked by the male head of the household, while *hourw* represents the annual number of hours worked by the wife. Thus, *Diff_Hours* represents the difference between hours worked by the husband and wife. A higher value of the variable indicates that the husband worked more hours relative to the wife, while lower values indicate less of a gap. This variable serves as a proxy for the share of income brought into the household by each parent. If the wife works for more hours, she may have more bargaining power within the household, giving her more of a say in the expenditure allocations.

In a similar manner, we define:

$$Diff\_Income = ly - wly,$$

where *ly* represents the husbands labour income, and *wly* represents the wife's. Thus, the variable *Diff_Income* represents the difference between the amount of income brought in by each parent. Higher values of the variable may proxy less bargaining power for the wife.

A description of all control variables is included in the Appendix of this paper.

5 Empirical Design

5.1 OLS

The central question of this paper is to determine how differences in economic and time-use dynamics within households influence family expenditure patterns. *Diff_Income*, shown in **Table 1**, captures disparities in financial contributions within households, which may reflect broader gender-based economic inequalities. *Diff_Hours*, shown in **Table 2**, focuses on differences in labor allocation and providing insights into how time-use dynamics within the household affect expenditure decisions. To explore these questions, this section introduces a series of Ordinary Least Squares models using a within fixed effects specification, also known as a two-way fixed effects model. This framework allows us to control for state-specific characteristics that remain constant over time as well as for year-specific shocks that may affect all states simultaneously.

The inclusion of state fixed effects is motivated by the possibility that certain states may exhibit unobservable but systematic differences that influence household spending. For instance, some states might have cultural norms that prioritize family expenditures, while others may provide more robust social safety nets or implement fiscal policies that affect household budgeting. By controlling for these unchanging state-level characteristics, we ensure that our analysis captures only within-state changes over time, rather than cross-state structural differences. Year fixed effects, on the other hand, are included to account for national-level shocks or policy changes that could impact expenditure patterns in a given year. Examples include periods of economic recession or growth, changes in federal taxation, or nationwide fiscal stimulus programs. Without these controls, such temporal shocks could confound the relationship between our key explanatory variables and household spending.

5.1.1 Controlled Models

To analyze the effect of *Diff_Income* on household expenditure proportions (*PropFExpense*), 8 models are specified with increasing sets of control variables. Each model includes state-level (*State FE*) and year-level (*Year FE*) fixed effects to account for time-invariant and common temporal shocks, respectively. The analysis employs the same set of models for both *Diff_Income* and *Diff_Hours*. Control variables are added incrementally, as follows:

$$\text{PropFExpense}_{it} = \beta_0 + \beta_1 \text{Diff\_Income}_{it} + \text{State FE}_i + \text{Year FE}_t + \epsilon_{it} \quad \text{(1) No Control Model}$$

$$\text{PropFExpense}_{it} = \beta_0 + \beta_1 \text{Diff\_Income}_{it} + \Gamma + \text{State FE}_i + \text{Year FE}_t + \epsilon_{it} \quad \text{(2) Demographic Controls}$$

$$\text{PropFExpense}_{it} = \beta_0 + \beta_1 \text{Diff\_Income}_{it} + \delta + \text{State FE}_i + \text{Year FE}_t + \epsilon_{it} \quad \text{(3) Employment Controls}$$

$$\text{PropFExpense}_{it} = \beta_0 + \beta_1 \text{Diff\_Income}_{it} + \gamma + \text{State FE}_i + \text{Year FE}_t + \epsilon_{it} \quad \text{(4) Financial Controls}$$

$$\text{PropFExpense}_{it} = \beta_0 + \beta_1 \text{Diff\_Income}_{it} + \Gamma + \delta + \text{State FE}_i + \text{Year FE}_t + \epsilon_{it} \quad \text{(5) Demographics \& Employment}$$

$$\text{PropFExpense}_{it} = \beta_0 + \beta_1 \text{Diff\_Income}_{it} + \Gamma + \gamma + \text{State FE}_i + \text{Year FE}_t + \epsilon_{it} \quad \text{(6) Demographics \& Financial}$$

$$\text{PropFExpense}_{it} = \beta_0 + \beta_1 \text{Diff\_Income}_{it} + \delta + \gamma + \text{State FE}_i + \text{Year FE}_t + \epsilon_{it} \quad \text{(7) Employment \& Financial}$$

$$\text{PropFExpense}_{it} = \beta_0 + \beta_1 \text{Diff\_Income}_{it} + \Gamma + \delta + \gamma + \text{State FE}_i + \text{Year FE}_t + \epsilon_{it} \quad \text{(8) Comprehensive Model}$$

In these equations, Γ represents demographic controls, which include variables such as the number of children, the age of the husband, age of the wife, the ethnic background, and whether the head of the household has a disability. δ represents employment controls, which capture employment status, self-employment status, and hours worked. Finally, γ represents financial controls, including expenditures on water, clothing, car insurance, car repair, gasoline, bus and taxi fares, medical visits (doctor, nurse, and prescriptions), and vacations. For a detailed understanding of the variables, please refer to the Appendix.

5.2 From Naive Machine Learning to Double Machine Learning

The analysis begins by considering the limitations of traditional Ordinary Least Squares (OLS) estimation in the context of our study. OLS relies on the assumption that the treatment variable, such as *Diff_Hours* or *Diff_Income*, is exogenous once control variables are included. However, in our context, where family expenditure decisions may be influenced by numerous unobserved factors such as regional economic conditions or family-specific preferences, this assumption is tenuous. Moreover, OLS is not equipped to handle high-dimensional covariates or to correct for potential biases that arise when the number of predictors approaches or exceeds the number of observations.

To address these issues, machine learning methods are introduced for their ability to model complex relationships and select relevant covariates. However, naive machine learning approaches introduce their own challenges. In the naive machine learning framework, the outcome variable Y is modeled as:

$$Y = D\hat{\theta}_0 + \hat{g}_0(X) + U,$$

where D is the treatment variable (e.g., *Diff_Hours*), X represents the covariates (e.g., demographic, employment, and financial controls), and $\hat{g}_0(X)$ captures the effect of X on Y. In this approach, machine learning algorithms are used iteratively to predict $\hat{g}_0(X)$ from $(Y - D\hat{\theta}_0) = g_0(X) + \epsilon$ and subsequently estimate $\hat{\theta}_0$ using OLS. However, this method suffers from two critical biases: overfitting, which can distort the estimation of $g_0(X)$, and regularization bias, which arises when the machine learning algorithms shrink estimates to reduce variance.

Given these limitations, DML provides a more robust framework by using machine learning models to isolate the variation in D and Y that is orthogonal to X. This mitigates endogeneity and bias. In this approach, the treatment variable D is modeled as:

$$D = m_0(X) + V,$$

where $m_0(X)$ represents the component of the treatment variable D, such as *Diff_Hours*, that can be predicted based on the observed covariates X. In the context of this study, $m_0(X)$ captures how variations in hours worked are systematically related to factors like employment status (*empst*), financial resources (*water*, *clothing*), and other demographic characteristics. For instance, individuals in higher employment categories might have systematically different expenditure patterns and time allocations, which would influence their reported hours. Machine learning algorithms are employed to estimate $m_0(X)$ because they excel at identifying complex, non-linear relationships within high-dimensional data.

The residual variation $\hat{V} = D - \hat{m}_0(X)$ isolates the portion of D that is uncorrelated with X, effectively creating a "clean" version of D that is free from confounding influences of the covariates, or "noise". This step marks a significant improvement over naive machine learning, where D and Y are modeled directly without properly accounting for the endogeneity introduced by X. Naive machine learning would allow D and X to potentially overfit the data, introducing regularization bias when the algorithm penalizes model complexity and reducing the validity of causal inference.

In contrast, double machine learning addresses this issue by decoupling the predictive power of the covariates X from the estimation of the treatment effect. By learning $m_0(X)$, the method ensures that only the exogenous variation in D, captured by $\hat{V}$, is used to estimate the causal effect. This is particularly advantageous in our setting, where expenditure proportions might be driven by unobservable heterogeneity across households or regions. By focusing only on the variation in D that is unrelated to these covariates, the approach mitigates the risk of spurious correlations and provides a more credible estimate of how differences in hours worked impact family expenditure patterns. **The DML algorithm used in our analysis is applied to the same model specifications used in the OLS estimation**. The resulting estimates provide a clearer understanding of the factors influencing family expenditure decisions, aligning with the study's goal of disentangling the effects of income and time constraints in a robust econometric framework. The results can be found in the upcoming Results section.

6 Results

6.1 Ordinary Least Squrares

The results presented in Tables 1 and 2 (appendix) provide a comparative view of the effects of income differences between husband and wife (*Diff_Income*) and hours worked differences (*Diff_Hours*) on family expenditure proportions across a range of models. Beginning with Table 1, it is evident that the treatment variable *Diff_Income* is not statistically significant in any of the models. This finding is consistent across all specifications, including the comprehensive Model 8. Such a result aligns with previous research on intra-household resource allocation, which has highlighted the potential insignificance of income disparities in developed economies like the United States. Unlike in developing countries, where income differences may lead to pronounced effects due to resource scarcity, the context of the United States suggests that households may employ compensatory mechanisms to smooth income disparities. This neutralizes their impact on expenditure allocation. These findings warrant a closer look at household dynamics in higher-income contexts, where factors beyond income differences – credit access, subsidized benefits, higher investments – might drive spending decisions.

Conversely, Table 2 reveals a different pattern for *Diff_Hours*. While the baseline model and many of the initial models fail to show statistical significance for the treatment variable, *Diff_Hours* becomes statistically significant in Models 6 and 7. This significance, emerging in more complex models that incorporate financial and employment controls, suggests that hours worked differences may interact meaningfully with these additional factors to influence family expenditure patterns. The finding underscores the importance of considering the broader household context when analyzing labour dynamics. Disparities in hours worked may reflect deeper behavioral and structural mechanisms, such as shifts in bargaining power within the household or differing responsibilities. For instance, households with unequal hours might increase spending on convenience goods and services to compensate for the reduced time availability of one member.

Zooming in on the control variables in both tables provides further insights. In Table 1, where *Diff_Income* remains consistently insignificant, variables like *Kids* and *Self3* (indicating individuals fully self-employed) are statistically significant in several models. The significance of *Kids* suggests that demographic composition plays a role in shaping expenditure allocation, likely due to the increased financial demands associated with children. Similarly, the effect of *Self3* may reflect the unique financial pressures and expenditure patterns of individuals who are fully self-employed, such as irregular income flows and higher business-related costs. Moreover, *Self2*, which represents individuals engaged in both employment and self-employment, and *Self9*, which denotes individuals who are not self-employed, show consistent statistical significance across Models 5, 6, and 8 in Table 2. The significance of *Self2* likely reflects the financial obligations these individuals face, which balances the responsibilities of self-employment with the income stability provided by external employment. This dual engagement may result in distinct spending behaviors, such as allocating resources toward both entrepreneurial activities and household expenditures. Similarly, the statistical significance of *Self9* suggests that households reliant on non-self-employed income streams exhibit specific expenditure patterns, potentially driven by greater predictability in income flows.

Table 2 introduces an interesting dynamic with *Hours* and *Empst3* (employment status = 3, indicating unemployment or actively seeking work) becoming significant in Model 3. The significance of *Hours* points to the direct relationship between time allocation and expenditure patterns, potentially driven by the trade-offs between time and money in household decision-making. For example, a member working fewer hours might result in higher expenditures on childcare or household services to compensate for their reduced availability. On the other hand, the significance of *Empst3* may reflect the distinct spending behavior of unemployed households, where limited financial resources could necessitate careful allocation of expenditures.

The patterns observed across the two tables reveal a key divergence in the statistical significance of *Diff_Income* and *Diff_Hours*, shedding light on the distinct ways income and labour dynamics influence household behavior. While *Diff_Income* fails to achieve significance in the U.S. context, this result may reflect the greater prevalence of mechanisms that smooth income disparities within households. In contrast, *Diff_Hours* emerges as a significant driver of expenditure patterns, particularly in Models 6 and 7, where labour market and financial controls are introduced. This finding underscores the critical role of time allocation within households and suggests that differences in hours worked—and the opportunity costs they entail—shape consumption decisions more profoundly than variations in income. The interaction between hours worked and other factors, such as employment status and specific financial behaviors, highlights the multidimensional nature of household decision-making and emphasizes the importance of accounting for these dynamics in understanding expenditure patterns.

6.2 Double Machine Learning

Now, we turn to Table 3 in the Appendix, which presents the estimation results from the Double Machine Learning framework. The table is divided into two panels: Panel A summarizes the results for the treatment variable *Diff_Hours*, while Panel B presents those for *Diff_Income*. Comparing these results with the corresponding OLS tables (Tables 1 and 2), we observe key differences that underscore the advantages of the DML approach.

Starting with Panel A, the estimates for *Diff_Hours* demonstrate that Double Machine Learning provides more precise and consistent estimates of the average treatment effect across different models. For example, in Model 7, the estimated effect of *Diff_Hours* is 0.000110 and statistically significant at the 5% level, with a corresponding p-value of 0.0018. This would mean that each additional hour of difference increases the proportion of household expenditures allocated to family expenses by 0.00011 units. As an example, shifting from part-time to full-time work (20 hours per week to 40 per week) would increase the number of hours worked annually by an individual by 1040 hours (52 $\times$ 20 hours per week) over the year. This would increase the proportion of family expenses by 1040 $\times$ 0.00011 = 0.1144 units.

In contrast, the OLS results in Table 2 show higher variability in the coefficient estimates, with less frequent statistical significance. This difference can be attributed to the ability of Double Machine Learning to flexibly account for the confounding effects of high-dimensional covariates, effectively reducing bias caused by omitted variables or model misspecification. Moreover, the Double Machine Learning estimates generally exhibit smaller standard errors compared to OLS. This improvement is particularly evident in Model 8, where the standard error of *Diff_Hours* is 0.00094 under Double Machine Learning, as opposed to 0.00116 in OLS. This reduction in uncertainty highlights the robustness of Double Machine Learning in controlling for endogenous treatment assignment, especially when working with observational data where traditional methods may struggle to isolate causal effects.

Turning to Panel B, which focuses on *Diff_Income*, we observe similar patterns. For instance, the estimates from Double Machine Learning in Model 7 are positive (6.41e-08) but not statistically significant, as the p-value exceeds 0.1. This lack of statistical significance mirrors the results in Table 1 under OLS, suggesting that the average treatment effect of *Diff_Income* on the outcome variable is either negligible or not well captured by the available data and controls. However, the consistency of the Double Machine Learning estimates across models reinforces the robustness of these findings, as the approach systematically adjusts for potential biases arising from high-dimensional covariates.

It is noteworthy that in Model 6, which includes demographic and financial controls, we find a statistically significant positive point estimate for the treatment effect of *Diff_Hours*. This result stands in contrast to our initial expectations, as prior research has often suggested that an increase in the wife's income generally leads to an increase in family expenditure. However, the positive coefficient estimated from our model indicates that as the difference in hours worked between the husband and wife increases (i.e., when the husband works more than the wife), family expenditure increases. This finding highlights an important distinction between developed and developing countries. It suggests that the mechanisms underlying household consumption patterns may differ significantly depending on the broader socioeconomic context. In developed countries, gender dynamics and economic factors are likely shaped by different influences compared to developing countries.

7 Conclusion

The findings presented in this paper provide a clear understanding of how intra-household disparities in income and time allocation shape family expenditure patterns. The results reveal a clear divergence in the significance of *Diff_Income* and *Diff_Hours*, with income differences demonstrating limited explanatory power in the U.S. context, while differences in hours worked emerge as a significant determinant of spending decisions in several models. This divergence underscores the importance of considering the broader socioeconomic context when analyzing household dynamics. In a developed economy like the United States, compensatory mechanisms such as credit access, stable employment, and institutional safety nets may neutralize the impact of income disparities, thereby diminishing their role in influencing household expenditures. In contrast, disparities in hours worked likely reflect deeper structural and behavioral factors, such as time availability, bargaining power within households, and labor market participation. These findings emphasize the need to account for the multidimensional nature of household decision-making.

The application of Double Machine Learning further enhances the robustness of these results by addressing the limitations of traditional econometric techniques. By using machine learning to isolate exogenous variation in the treatment variables, this approach provides more reliable estimates of the causal effects of *Diff_Income* and *Diff_Hours* on family expenditure proportions. The findings highlight the significance of *Diff_Hours*, particularly in models that incorporate demographic, employment, and financial controls. These results contribute to a growing body of literature that seeks to understand the complex dynamics of household decision-making.

8 Limitations

While this paper offers valuable insights into the determinants of family expenditure patterns, several limitations should be noted. First, the analysis is constrained by the nature of the outcome variable, *PropFExpense*, which represents the proportion of family expenditures relative to household income. This specification implicitly assumes that richer households will spend a larger fraction of their income on consumption, which may not hold in practice. Wealthier families often exhibit diminishing marginal propensity to consume, capping their expenditure proportions despite higher absolute incomes. Although this issue is partially mitigated by dividing expenditures by income to create a per capita measure, it remains a potential source of bias in the analysis. Future research could address this limitation by exploring alternative outcome variables that better capture the variability in consumption patterns across income levels.

Second, the analysis does not fully account for unobservable family-specific preferences, such as cultural norms, that may influence both income and time allocation decisions. While the inclusion of state and year fixed effects helps control for broader contextual factors, these fixed effects cannot capture within-family heterogeneity that may drive expenditure patterns. Finally, the study is limited by its focus on the United States, a high-income context with well-developed financial and institutional infrastructure. The findings may not generalize to lower-income countries, where income disparities and labor dynamics likely play a more prominent role in shaping household behavior.

Third, the study is limited by its focus on the United States, a high-income context with well-developed financial and institutional infrastructure. While the U.S. provides a valuable example of a developed nation, it may not represent the ideal benchmark for examining this issue in the broader context of developed countries. The U.S. ranks differently from other developed nations on indices such as the Human Development Index and the Gini Coefficient, which implies potential disparities in economic equality and development levels. Other countries like Monaco, Switzerland, Ireland, and Norway, which consistently perform better in terms of income equality and human development, may provide more insightful benchmarks for examining household expenditure patterns. Countries that provide universal healthcare to their citizens may be better economies to examine, as the lack of healthcare expenditures may change the decision-making context of economic agents. Thus, focusing exclusively on the U.S. may limit the generalizability of the findings even among high-income countries. This suggests a need for future research that includes a more diverse set of developed country contexts for a comprehensive understanding of these dynamics.

9 Critical Discussion

Beyond its economic implications, this study invites reflection on broader societal dynamics that shape household behavior. The observed significance of *Diff_Hours* highlights the centrality of time as a resource in modern economies. Time is not only a factor of production but also a key determinant of quality of life, shaping how individuals balance work, leisure, and family responsibilities. Disparities in hours worked within households may reflect underlying inequalities in labor market access, caregiving responsibilities, or social expectations, raising important questions about equity and well-being. For instance, households with unequal time allocations may experience heightened stress or reduced cohesion, as one member shoulders a disproportionate burden of economic or domestic work. Addressing these disparities requires policies that promote work-life balance, such as flexible working arrangements and affordable childcare, which could alleviate the pressures associated with unequal time allocation.

Furthermore, the findings prompt a critical examination of the role of gender in shaping household dynamics. Differences in hours worked often correlate with gendered patterns of labor, where women are more likely to engage in unpaid domestic work, while men contribute more to market labor. These patterns perpetuate structural inequalities, limiting women's economic opportunities and bargaining power within households. Tackling these issues requires not only economic interventions but also cultural shifts that challenge traditional gender roles and promote shared responsibilities within families.

Lastly, this study highlights the importance of integrating interdisciplinary perspectives into the analysis of household behavior. While the econometric framework provides a rigorous tool for isolating causal effects, understanding the full complexity of household decision-making requires insights from sociology, psychology, and political science. For example, the role of trust and cooperation within households, the impact of societal norms on labor market participation, and the influence of political institutions on resource allocation are all critical factors that extend beyond the scope of this study. By engaging with these broader dimensions, future research can provide a more holistic understanding of the factors that drive household behavior. This may help contribute to policies that promote economic equity and social well-being.

10 Appendix

10.1 References

Senauer, B., Garcia, M., Jacinto, E. (1988). Determinants of the intrahousehold allocation of food in the rural Philippines. *American Journal of Agricultural Economics, 70*(1), 170–180. `https://doi.org/10.2307/1241987`

Thomas, D. (1994). Like father, like son; like mother, like daughter: Parental resources and child height. *The Journal of Human Resources, 29*(4), 950. `https://doi.org/10.2307/146131`

Deschênes, S., Dumas, C., & Lambert, S. (2020). Household resources and individual strategies. *World Development, 135*, 105075. `https://doi.org/10.1016/j.worlddev.2020.105075`

Haushofer, J., & Shapiro, J. (2016). The short-term impact of unconditional cash transfers to the poor: Experimental evidence from Kenya*. *The Quarterly Journal of Economics, 131*(4), 1973–2042. `https://doi.org/10.1093/qje/qjw025`

Kenayathulla, H. B. (2016). Gender differences in intra-household educational expenditures in Malaysia. *International Journal of Educational Development, 46*, 59–73. `https://doi.org/10.1016/j.ijedudev.2015.10.007`

10.2 Control Variables

- Γ: Vector of demographic controls including the number of children, the age of the wife, and the ethnic background of the family.
  - *race*: Proxy for ethnic background of the family. Takes value = 1 if white, = 2 if black, = 3 if Spanish-American, = 7 if other.
- δ: Vector of employment controls, including employment status, self-employment status, and hours worked.
  - *empst*: Record of employment status of the head of the household. Takes value = 1 if working now, = 2 if temporarily laid off, = 3 if unemployed and looking for work, = 4 if retired, = 5 if permanently disabled, = 7 if student, = 8 if other.
  - *self*: Record of self-employment of the head of the household. Takes value = 1 if works for someone else, = 2 if works for someone else and self, = 3 if works for self only, = 0 if unemployed/retired/disabled.
- γ: Vector of financial controls, including expenditures on water, clothing, car insurance, car repair, gasoline, bus and taxi fares, medical visits (doctor, nurse, and prescriptions), and vacations.

10.3 Tables

See the following pages.

Table 1: Estimation Results for the Impact of Income Differences (Diff_Income) on Family Expenditure Proportion
OLS Fixed Effect Within Model (Two-Way Effect Model)

Dependent Variable: PropFExpense	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Diff_Income	-0.000005	-0.000005	0.0000003	-0.000021	0.000006	0.000001	0.000010	0.000006
(Standard Error)	(0.000007)	(0.000007)	(0.000001)	(0.000014)	(0.000007)	(0.000014)	(0.000012)	(0.000014)
Controls:								
Demographic Controls	No	Yes	No	No	Yes	Yes	No	Yes
Employment Controls	No	No	Yes	No	Yes	No	Yes	Yes
Financial Controls	No	No	No	Yes	No	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,593	10,593	9,950	5,418	10,586	5,418	5,094	5,418
R-squared	0.00004	0.00004	0.00328	0.00463	0.01256	0.02277	0.02412	0.02278
Statistically Significant Variables (Controls):	None	Kids (*)	Hours (**) empst3 (***)	Water (**) Clothing (**)	Kids (*) Self3 (*) Self9 (*)	Water (**) Clothing (**) Self2 (**) Self3 (**)	Water (**), Self3 (**)	Kids (*) Water (**) Clothing (*) Self1 (**) Self3 (**) Self9 (**)

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
The results are based on OLS Fixed Effect Within Models (Two-Way Effect Model) accounting for both state and year fixed effects.

Table 2: Estimation Results for the Impact of Hours Differences (Diff_Hours) on Family Expenditure Proportion
OLS Fixed Effect Within Model (Two-Way Effect Model)

Dependent Variable: PropFExpense	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Diff_Hours	-0.00044	-0.00050	0.00016**	-0.00105	-0.00105	0.00283*	0.00308	0.00284*
(Standard Error)	(0.00043)	(0.00044)	(0.00008)	(0.00084)	(0.00084)	(0.00113)	(0.00116)	(0.00116)
Controls:								
Demographic Controls	No	Yes	No	No	Yes	Yes	No	Yes
Employment Controls	No	No	Yes	No	Yes	No	Yes	Yes
Financial Controls	No	No	No	Yes	No	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,593	10,593	9,950	5,418	5,418	5,418	5,094	5,418
R-squared	0.00001	0.00007	0.00364	0.00447	0.00447	0.02391	0.02412	0.02391
Statistically Significant Variables (Controls):	None	Kids (*)	Hours (**) empst3 (***)	Water (**) Clothing (**)	Kids (*) Self3 (*) Self9 (*)	Water (**) Clothing (**) Self2 (**) Self3 (**)	Water (**), Self3 (**)	Kids (*) Water (**) Clothing (*) Self1 (**), Self3 (**), Self9 (**)

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
The results are based on OLS Fixed Effect Within Models (Two-Way Effect Model) accounting for both state and year fixed effects.

Table 3: Double Machine Learning Estimation Results for the Impact of Diff_Hours and Diff_Income
OLS Fixed Effect Within Model (Two-Way Effect Model)

Dependent Variable: PropFExpense	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Panel A: Treatment Variable = Diff_Hours							
Estimate	0.0006684	0.00135	-0.00129	0.00098	0.00158	0.000110**	0.00162
Std. Error	(0.00036)	(0.00081)	(0.00088)	(0.00085)	(0.00095)	(0.00036)	(0.00094)
t-value	-1.83	1.66	-1.48	1.11	1.66	3.12	1.74
p-value	0.067	0.096	0.140	0.268	0.096	0.0018**	0.0825
Panel B: Treatment Variable = Diff_Income							
Estimate	-4.92e-06	8.67e-06	-3.15e-05	3.86e-06	2.36e-05	6.41e-08	1.05e-05
Std. Error	(2.62e-06)	(5.47e-06)	(1.95e-05)	(4.66e-06)	(1.53e-05)	(1.37e-07)	(9.33e-06)
t-value	-1.88	1.58	-1.62	0.83	1.54	0.47	1.12
p-value	0.061	0.113	0.106	0.407	0.123	0.639	0.263

Notes: Panel A summarizes results for Diff_Hours as the treatment variable, while Panel B reports results for Diff_Income. Standard errors are in parentheses. ** $p<0.05$, * $p<0.1$.