Commuting, Wages, and Household Decisions

José Ignacio Giménez-Nadal[1,2], José Alberto Molina[1,2], and Jorge Velilla*[1,2]

[1]IEDIS, University of Zaragoza, Zaragoza, Spain

[2]Global Labor Organization (GLO), Berlin, Germany

March 27, 2025

Abstract

This paper develops a household-level model of commuting that allows to examine how commuting time, wages, labor supply, and consumption decisions interact within the household, and extends traditional urban and labor market models. The theoretical model integrates static and life-cycle perspectives and allows us to examine commuting patterns both across households and within households over time. We employ PSID data and address the potential endogeneity between commuting time and wages using GMM. Our findings indicate that, while cross-sectional analyses suggest a positive correlation between wages and commuting, this relationship weakens significantly when adjusting for household heterogeneity and endogeneity. Additionally, we highlight a positive correlation between commuting time and consumption, and between the spouses' commuting times. We further document how commuting patterns evolve over the life cycle, with household wealth reducing commuting durations while higher earnings increase them. Our results contribute to the literature on gender gaps, labor mobility, and urban economics by providing a household perspective on commuting and labor market outcomes.

Keywords: Commuting; household behavior; wages; PSID.
JEL classification: D12; D15; J22; J31.

*Corresponding author at: Department of Economic Analysis, University of Zaragoza, C/ Gran Vía 2, 50005 Zaragoza, Spain.
E-mails: Giménez-Nadal: ngimenez@unizar.es, Molina: jamolina@unizar.es, Velilla: jvelilla@unizar.es.
Acknowledgments: This work was supported by the Government of Aragón [Project S32_23R, Program FSE Aragón 2014-2020]. This paper was partially written while José Alberto Molina was Visiting Scholar at the Department of Economics of Boston College (US), to which he would like to express his thanks for the hospitality and facilities provided.
Declaration of Competing Interest: None.

1 Introduction

This paper develops a household-level model of commuting that integrates both static and life-cycle perspectives to examine the interactions between commuting time, wages, labor supply, and consumption decisions, extending traditional urban and labor market models. A substantial body of research has documented persistent gender disparities in labor market outcomes, particularly in earnings (Olivetti and Petrongolo, 2016; Olivetti et al., 2024). Women, on average, earn lower wages than men, and this gender wage gap has been attributed to several mechanisms, including differences in time flexibility (Bertrand et al., 2010; Goldin, 2014), occupational segregation (Blau and Kahn, 2017), gender roles (Fortin, 2005, 2015), and the child penalty (Kleven and Søgaard, 2019). Hsieh et al. (2019) suggest that closing the gender wage gap could increase economic output by 20% to 40% through a more efficient allocation of talent. An additional factor that has gained attention in recent years is the role of commuting. Studies show that women systematically choose shorter commuting times than men (Giménez-Nadal et al., 2022), which may reflect a greater willingness to pay for proximity to home, potentially at the expense of earnings (Petrongolo and Ronchi, 2020; Le Barbanchon et al., 2021). Examining how commuting choices shape labor market outcomes is essential for understanding the persistence of gender wage disparities. We extend the study of commuting by incorporating a household perspective, an approach that has not been fully explored in the literature and that allows us to analyze gender differentials in factors affecting commuting.

Economic theory on commuting behavior has been extensively developed within the frameworks of urban economics, labor supply models, and job-search theory. Traditional urban economic models, such as Ross and Zenou (2008), emphasize individual utility maximization, where workers balance commuting costs against wage benefits. In these models, commuting time is treated as a shock to workers' time allocation that has an opportunity cost, and workers adjust their commuting decisions to optimize their overall well-being. Labor supply models provide another important perspective, incorporating commuting time into the standard labor-leisure trade-off framework. In these models, workers allocate their time between paid work, commuting, and leisure, taking into account how commuting costs—both monetary and in terms of lost leisure—affect labor supply decisions (Cogan, 1981). A key implication is that higher commuting costs may lead to adjustments in work hours, job choices, or labor market participation, particularly for individuals with greater household responsibilities (Ehrenberg and Smith, 2003; Manning, 2003). Additionally, job-search models, like those presented by Van Ommeren and van der Straaten (2008) and Le Barbanchon et al. (2021), focus on how workers search for and accept jobs with different commuting requirements. For instance, Le Barbanchon et al. (2021) integrate the spatial dimension of job searches, suggesting that workers trade off the expected wage gain from a new job against the commuting cost, with the potential for job-matching frictions influencing commuting decisions.

Gender differences in commuting can be explained through several economic and gender theories. First, the theory of gender discrimination suggests that women may face discrimination in the labor market, influencing their commuting decisions by limiting access to higher-paying jobs or jobs located farther away from home (Becker, 1957). Second, time-use theory posits that women, due to their higher domestic workload, tend to prefer jobs closer to home to minimize commuting time, balancing paid work with household responsibilities (Folbre, 2001), including the child penalty (Kleven and Søgaard, 2019). Third, occupational segregation theory highlights that women and men are often employed in different sectors, which can lead to divergent commuting patterns, as women may be concentrated in jobs closer to home in urban areas (Polachek, 1981). Additionally, social and economic mobility theory suggests that women's lower economic mobility, due to childcare or caregiving responsibilities, may restrict their commuting distance and job opportunities (Cohen, 2013). Lastly, economic autonomy theory indicates that women with greater financial independence and flexibility are more likely to accept jobs that require longer commutes, while those with lower economic autonomy may prefer nearby work options due to economic or familial constraints (Anderson, 2012).

We extend the study of commuting by incorporating a household perspective, an approach that has not been fully considered in the literature. By integrating recent advancements in household economics (e.g., Blundell et al., 2016), we develop a household-level model of commuting that enables us to examine how spouses' commuting times, wages, labor supplies, and consumption decisions interact within the household. This framework captures the interdependent decisions of household members, providing a more comprehensive analysis of commuting behaviors within households, and their implications for labor market outcomes, including the potential gender disparities in commuting patterns. While the existing literature has recognized the significance of intra-household dynamics when studying commuting, empirical studies have often focused on individual worker samples, neglecting the complexities of household behaviors due to the scarcity of detailed household longitudinal data. Exceptions include the works of Roberts et al. (2011) and De Palma et al. (2015), who analyze commuting and well-being, and coordinated commuting behaviors, respectively. Other studies have explored the gender gap in commuting time and distance (Casado-Díaz et al., 2023), and the relationship between commuting and household composition (McQuaid and Chen, 2012; Jacob et al., 2019; Neto et al., 2015). Our model allows us to investigate these dynamics, providing insights into how household members choose their commuting patterns and the gender differences in these choices. This has important implications for understanding labor market outcomes.

We propose a theoretical model that integrates both static and life-cycle perspectives, enabling a deeper understanding of the factors that shape commuting behaviors in dual-earner households. This model allows us to examine commuting patterns both across households and within households over time. We derive the optimality conditions of the model under both static and life-cycle frameworks. A key aspect of our model is its ability to analyze cross-spouse effects, exploring how one spouse's commuting time and labor supply decisions impact the other's commuting behavior and overall commuting dynamics. This paper investigates the interactions between these factors and discusses the broader economic and societal implications of these interdependencies.

We use data from the Panel Study of Income Dynamics (PSID) covering the period from 2011 to 2019 in the US, when commuting time data became available. Our sample is restricted to households with married or unmarried couples where both spouses are employed, reporting positive labor market outcomes such as work hours, wages, and commuting time. We estimate the log-linearized optimality conditions of the model using GMM, accounting for the interdependence of the variables and potential correlations between error terms. A crucial aspect of our empirical strategy is addressing endogeneity between wages and commuting time. To do this, we instrument wages using a Mincer-style equation similar to Blundell et al. (2016), but including individuals' quarter of birth, which affects human capital accumulation but is unlikely to be correlated with unobserved factors influencing commuting decisions. This instrumental variable approach helps isolate the causal relationship between wages and commuting time.

The results of our analysis reveal several important insights into the relationships between household behaviors, commuting, and labor market outcomes. In line with previous research, we initially observe a positive cross-sectional correlation between spouses' wages and commuting times, with a 10% increase in wages leading to a 2.5% to 3.2% increase in commuting time. This finding is consistent with studies that have explored the relationship between wages and commuting behavior. For example, Chandra and Thompson (2000) find that a 10% increase in wages is associated with a 2.5% increase in commuting time. Similarly, Hansen (2005), Dube and Chalavan (2015) and Glaeser and Kahn (2004) shows that a 10% increase in wages leads to a 3.2%, 2.8% and 2.5% increase in commuting time, respectively. However, this correlation weakens significantly once we account for endogeneity between commuting and wages, and disappears when we net out unobserved heterogeneity or estimate first-difference equations. These results suggest that the positive correlation observed in cross-sectional studies would be driven by unobserved household characteristics, rather than a direct causal relationship between wages and commuting.

Furthermore, our analysis reveals that household factors are relevant in explaining commuting behaviors. For instance, household expenditures are positively related to spouses' commuting times, and the cross-correlation between spouses' commuting times is positive and highly significant. We also find that household earnings and wealth relate to the dynamics of spouses' commuting times, as household earnings correlate positively with the growth rate of commuting times, while household wealth is associated with decreased commuting time. Despite that, while the correlations between spouses' commuting times, consumption, and work hours are relevant in the cross-section, the dynamics of spouses' commuting times are relatively stable and do not appear to be significantly influenced by changes in other household behaviors.

Our contribution to the literature posits our paper at the intersection of labor economics, urban economics, and household decision-making, providing a novel perspective on the interconnectedness of spouses' commuting times, wages, and household behavior. First, our paper extends the traditional urban and job-search models of commuting by developing a household-level framework that explicitly accounts for intra-household interactions in commuting decisions. While previous studies have examined individual commuting behaviors and their trade-offs with wages (e.g., Le Barbanchon et al., 2021), our analysis provides new insights into how spouses coordinate commuting, labor supply and consumption decisions. This approach allows us to analyze the role of gender in shaping commuting behavior, building on the literature that highlights gender-specific preferences for job location and flexibility (Petrongolo and Ronchi, 2020). By considering both cross-sectional and life-cycle perspectives, we also offer a comparison of differences across households, and a dynamic approach to how commuting time evolves over time.

Second, while prior work has documented gender disparities in commuting patterns and labor market attachment (Illing et al., 2024), our study contributes by explicitly modeling how commuting behaviors evolve over time within households. We find that household earnings are positively correlated with changes in commuting time, whereas household wealth tends to reduce commuting durations. However, wages and other household behaviors do not relate to changes in spouses' commuting times. This suggests that commuting decisions are relatively stable over the households' life cycle, but can evolve with changes in household financial stability. Our life-cycle framework enhances the literature on job mobility and urban labor markets by demonstrating that household constraints, rather than individual preferences alone, shape commuting patterns over time.

Third, we address the endogeneity between wages and commuting time by using workers' quarter of birth as an instrumental variable. Existing research has shown that individuals trade off longer commutes for higher wages (e.g., see Dauth et al., 2022, for a recent analysis), but these studies often rely on cross-sectional evidence that may not fully capture unobserved heterogeneity. Our findings suggest that the observed positive correlation between wages and commuting time in cross-sectional analyses largely disappears when accounting for household-level heterogeneity and endogeneity. This aligns with recent evidence on labor market frictions and spatial mismatches but adds a novel dimension by considering household decision-making.

The remainder of the paper is structured as follows. Section 2 presents the model and derives the equations for estimation. Section 3 details the data employed in the analysis and outlines the econometric strategy. Section 4 presents the primary findings from the static reduced form approach (4.1), and the quasi-reduced form life cycle approach (4.2). Section 5 discusses these results, and finally Section 6 concludes.

2 Model

In this section, we introduce a model that characterizes household behavior, focused on households composed of two working spouses.

2.1 The setting

Assume that a household j is formed by working spouses $i = 1, 2$, and lives for periods $t = 0, \dots, T$.[1] The model assumes that the household derives utility from consumption q_t and housing expenditure H_t, while experiencing disutility from each spouse's market work hours h_{it} and commuting time c_{it} (Van Ommeren and Fosgerau, 2009). The utility function is a well-behaved function:

$$U_t = U\left(H_t, q_t, c_{1t}, c_{2t}, h_{1t}, h_{2t}; \boldsymbol{x}_t\right),$$

satisfying the conditions $\partial U_t/\partial H_t > 0$, $\partial U_t/\partial q_t > 0$, $\partial U_t/\partial c_{it} < 0$, and $\partial U_t/\partial h_{it} < 0$, $i \in \{1, 2\}$. The term $\boldsymbol{x}_t$ represents a vector of taste observables.

[1]We omit subscript j throughout the model for simplicity.

The model constrains the household to a budget, wherein wages and commuting are interrelated (e.g., urban efficiency wages, wage premia, specialization, etc.).[2] This interrelation implies that spouses' commuting times factor into the budget constraint, affecting labor earnings. If w_{it} represents the wage of spouse $i \in \{1, 2\}$, then household labor earnings are defined as:

$$y_t = w_{1t}h_{1t} + \eta_{1t}c_{1t} + w_{2t}h_{2t} + \eta_{2t}c_{2t},$$

where η_{it} represents the relationship between spouse i earnings and commuting time. Commuting enters the budget constraint as part of income because many studies have reported wage premia associated with longer commutes (see, e.g., Leigh, 1986; Van Ommeren et al., 2000; Albouy and Lue, 2015, among others). This potentially reflects firms' compensation for commuting-related disutility. Hence, the presence of η_{it} in the budget constraint indicates a direct link between wages and commuting times. For instance, if employers provide compensation for longer commutes, then $\eta_{it} > 0$. Conversely, if wages and commuting are not related, then $\eta_{it} = 0$.

Assuming the price of consumption is normalized to 1, and denoting the interest rate by r, the household faces the following budget constraint:

$$H_t + q_t + a_{t+1} = y_t + (1 - r)a_t, \tag{1}$$

where a_t represents savings and assets. The household's period t decision variables are then represented by the set $\Theta_t = \{H_t, q_t, c_{1t}, c_{2t}, h_{1t}, h_{2t}, a_{t+1}\}$.

Household utility and the budget constraint both capture elements of urban models of commuting as housing, with commuting being potential related to earnings or the trade-off between housing and commuting in a monocentric city (Alonso, 1964; Mills, 1967). Monocentric city models assume that jobs concentrate in the core of the city – a so-called central business district – and workers have to decide where to live influenced by commuting costs and housing costs. Commuting costs increase as workers live further away from the business district, and at the same time housing costs decrease as one moves further from the city center (i.e. the business district). This trade-off has implications for housing choices and urban sprawl, among others. See recent investigations by Huai et al. (2021) and Liotta et al. (2022).[3]

In this household model, the potential trade-off between commuting and housing is re-

[2] We remain agnostic regarding the channels that relate commuting and wages. We aim at measuring relationships, therefore we do not need to develop a fully specified model, which is left for further research.

[3] Commuting has also been studied from the perspective of spatial economics. See Severen (2023) for a recent review.

flected similarly. The household utility function explicitly assumes that workers dislike commuting and enjoy housing, as in urban models. Thus, households should look to reside in the business district (i.e., very short commutes, and the same time should look to reside in places with the best amenities. Besides that, the budget constraint is also dependent on both housing and commuting. On one hand, the more money spent on housing, the less available for consumption, which also produces utility to households. On the other hand, firms *might* pay compensation wages to workers with long commutes. This generates trade-offs and therefore a potential relationship not only between housing and commuting, but between all the key endogenous variables of the model.

Household program The household aims to maximize its utility over the finite time horizon, solving the following program:

$$\max_{\{\Theta_t\}_{t=0}^{T}} \sum_{t=0}^{T} \beta^t U\left(H_t, q_t, c_{1t}, c_{2t}, h_{1t}, h_{2t}; \boldsymbol{x}_t\right) \tag{2}$$
$$\text{s.t.: the budget constraint (1), } \forall t.$$

Here, β denotes the discount factor. Following Blundell et al. (2016), we characterize the household's optimal behavior through the intra-temporal first order conditions of (2). To do this, we first define the Lagrangian:

$$\mathcal{L} = \sum_{t=0}^{T} \Big\{ \beta^t U_t + \lambda_t \big((1-r)a_t + y_t - H_t - q_t + a_{t+1} \big) \Big\}.$$

For convenience, assume that $U_t = \tilde{U}\left(\tilde{H}_t, \tilde{q}_t, \tilde{c}_{1t}, \tilde{c}_{2t}, \tilde{h}_{1t}, \tilde{h}_{2t}\right)$, where $\tilde{x} = xe^{-\boldsymbol{x}'_{it}\xi^x_{it}}$, for $x = H_t, q_t, c_{it}, h_{it},\ i \in \{1,2\}$. This allows us to compute the intra-temporal first order conditions at any period $t \geq 1$:[4]

$$\begin{aligned}
\tilde{U}_{[H]} \exp\left(-\boldsymbol{x}'_t \xi^H_t\right) &= \lambda_t, \\
\tilde{U}_{[q]} \exp\left(-\boldsymbol{x}'_t \xi^q_t\right) &= \lambda_t, \\
-\tilde{U}_{[c_i]} \exp\left(-\boldsymbol{x}'_{it} \xi^{c_i}_{it}\right) &= \lambda_t \eta_{it}, \quad i \in \{0,1\}, \\
-\tilde{U}_{[h_i]} \exp\left(-\boldsymbol{x}'_{it} \xi^{h_i}_{it}\right) &= \lambda_t w_{it}, \quad i \in \{0,1\}.
\end{aligned} \tag{3}$$

[4] $f_{[x_k]} = \partial f / \partial x_k$ for any function $f = f(x_1, \ldots, x_n)$ and $k = 1, \ldots, n$.

Development in a static, reduced form setting Taking logs, we can express the first order conditions (3) as:

$$\begin{aligned}
\log(\tilde{U}_{[H]}) &= \boldsymbol{x}_t^{'}\xi_t^H + \log\lambda_t, \\
\log(\tilde{U}_{[q]}) &= \boldsymbol{x}_t^{'}\xi_t^q + \log\lambda_t, \\
\log(-\tilde{U}_{[c_i]}) &= \boldsymbol{x}_{it}^{'}\xi_{it}^{c_i} + \log\lambda_t + \log\eta_{it}, \quad i \in \{0,1\} \\
\log(-\tilde{U}_{[h_i]}) &= \boldsymbol{x}_{it}^{'}\xi_{it}^{h_i} + \log\lambda_t + \log w_{it}, \quad i \in \{0,1\}.
\end{aligned}$$

Then again, partial derivatives of marginal utilities can be expressed in reduced form as functions of their arguments. That is to say, $\log(\tilde{U}_{[x]}) = f^x\left(H_t, q_t, c_{1t}, c_{2t}, h_{1t}, h_{2t}\right)$, for $x = H_t, q_t, c_{it}, h_{it}$, $i \in \{1,2\}$.

Hence, the optimality conditions in a static setting can be expressed, in reduced form and for $-i \neq i$, as:

$$\begin{aligned}
H_t &= H_t\left(\log\lambda_t, q_t, c_{1t}, c_{2t}, h_{1t}, h_{2t}, \boldsymbol{x}_t\right), \\
q_t &= q_t\left(\log\lambda_t, H_t, c_{1t}, c_{2t}, h_{1t}, h_{2t}, \boldsymbol{x}_t\right), \\
c_{it} &= c_{it}\left(\log\lambda_t, \log\eta_{it}, H_t, q_t, c_{-it}, h_{1t}, h_{2t}, \boldsymbol{x}_{it}\right), \quad i \in \{1,2\}, \\
h_{it} &= h_{it}\left(\log\lambda_t, \log w_{it}, H_t, q_t, c_{1t}, c_{2t}, h_{-it}, \boldsymbol{x}_{it}\right), \quad i \in \{1,2\}.
\end{aligned} \tag{4}$$

It is important to note that we allow for interdependence between the endogenous variables in the model. An alternative approach would assume separability, i.e. that the optimal decisions about how much labor to supply, how much time to commute, and how much to consume are made independently. We decided to allow for these interdependencies in the model, as the theoretical setting is partially based on trade-offs between commuting, housing, and the remaining endogenous variables.

Development in a dynamic setting On the other hand, taking logs and first difference, we can log-linearize (3) as:

$$\begin{aligned}
\Delta\log(\tilde{U}_{[H]}) &= \Delta\boldsymbol{x}_t^{'}\xi_t^H + \Delta\log\lambda_t, \\
\Delta\log(\tilde{U}_{[q]}) &= \Delta\boldsymbol{x}_t^{'}\xi_t^q + \Delta\log\lambda_t, \\
\Delta\log(-\tilde{U}_{[c_i]}) &= \Delta\boldsymbol{x}_{it}^{'}\xi_{it}^{c_i} + \Delta\log\lambda_t + \Delta\log\eta_{it}, \quad i \in \{1,2\}, \\
\Delta\log(-\tilde{U}_{[h_i]}) &= \Delta\boldsymbol{x}_{it}^{'}\xi_{it}^{h_i} + \Delta\log\lambda_t + \Delta\log w_{it}, \quad i \in \{1,2\}.
\end{aligned} \tag{5}$$

Next, we apply a standard log-linearization of $\tilde{U}_{[H]}$, $\tilde{U}_{[q]}$, $\tilde{U}_{[c_i]}$, and $\tilde{U}_{[h_i]}$, for $i \in \{1,2\}$, based on first order Taylor series.[5] We then can write the log-linearization of marginal utilities, in quasi-reduced form, as:

$$
\begin{aligned}
\Delta \log(\tilde{U}_{[H]}) &\approx \alpha_H H_{t-1}\Delta \log H_t + \alpha_q q_{t-1}\Delta \log q_t + \alpha_{c_1} c_{1t-1}\Delta \log c_{1t} \\
&\quad + \alpha_{c_2} c_{2t-1}\Delta \log c_{2t} + \alpha_{h_1} h_{1t-1}\Delta \log h_{1t} + \alpha_{h_2} h_{2t-1}\Delta \log h_{2t}, \\
\Delta \log(\tilde{U}_{[q]}) &\approx \beta_H H_{t-1}\Delta \log H_t + \beta_q q_{t-1}\Delta \log q_t + \beta_{c_1} c_{1t-1}\Delta \log c_{1t} \\
&\quad + \beta_{c_2} c_{2t-1}\Delta \log c_{2t} + \beta_{h_1} h_{1t-1}\Delta \log h_{1t} + \beta_{h_2} h_{2t-1}\Delta \log h_{2t}, \\
\Delta \log(-\tilde{U}_{[c_i]}) &\approx \gamma^i_H H_{t-1}\Delta \log H_t + \gamma^i_q q_{t-1}\Delta \log q_t + \gamma^i_{c_1} c_{1t-1}\Delta \log c_{1t} \\
&\quad + \gamma^i_{c_2} c_{2t-1}\Delta \log c_{2t} + \gamma^i_{h_1} h_{1t-1}\Delta \log h_{1t} + \gamma^i_{h_2} h_{2t-1}\Delta \log h_{2t}, \quad i \in \{1,2\}, \\
\Delta \log(-\tilde{U}_{[h_i]}) &\approx \delta^i_H H_{t-1}\Delta \log H_t + \delta^i_q q_{t-1}\Delta \log q_t + \delta^i_{c_1} c_{1t-1}\Delta \log c_{1t} \\
&\quad + \delta^i_{c_2} c_{2t-1}\Delta \log c_{2t} + \delta^i_{h_1} h_{1t-1}\Delta \log h_{1t} + \delta^i_{h_2} h_{2t-1}\Delta \log h_{2t}, \quad i \in \{1,2\}.
\end{aligned}
\tag{6}
$$

Assembling (5) and (6) together, we can obtain the equations that represent the first order conditions of program (2).

2.2 Estimating equations

Modeling choices We need to make some assumptions before we can explicitly present estimating equations, both in the reduced form and the life cycle settings. First, $\log \lambda_t$ is unobserved. We approach this by assuming it to be a polynomial on earnings and wealth as in Theloudis et al. (2025):

$$
\begin{aligned}
\log \lambda_t &\approx \rho_1 \log y_t + \rho_3 \log a_t, \\
\Delta \log \lambda_t &\approx \zeta_1 \log y_{t-1} + \zeta_2 \Delta \log y_t + \zeta_3 \log a_{t-1} + \zeta_4 \Delta \log a_t.
\end{aligned}
$$

Similarly, compensation rates for commutes are unobserved. We assume they can be represented as a function of wages, as follows:

$$
\begin{aligned}
\log \eta_{it} &\approx \eta_i \log w_{it}, \\
\Delta \log \eta_{it} &\approx \eta_i \Delta \log w_{it},
\end{aligned}
$$

where η_i is the unobserved factor that relate wages and commuting. An important remark is that wages are typically exogenous (e.g., right-hand-side) variables in household models (e.g.

[5] We follow a quasi-reduced form approach, as we do not focus on the deep structure of parameters. See Appendix A for details.

Chiappori et al., 2002; Mazzocco, 2007; Lise and Yamada, 2019). This contrasts with some general equilibrium urban models in which wages are typically left-hand-side variables, such as Ross and Zenou (2008), Ruppert et al. (2009) and Fu and Ross (2013). This represents a key difference of the household context with respect to urban and job-search models.

Static, reduced form setting In a pure reduced form and static approach, assuming a logarithmic specification, estimating commuting equations can be expressed, for $-i \neq i$, as:

$$\begin{aligned} \log c_{it} = \gamma_0^{c_i} + \eta_i \log w_{it} + \gamma_y^{c_i} \log y_t + \gamma_a^{c_i} \log a_t + \gamma_H^{c_i} \log H_t + \gamma_q^{c_i} \log q_t \\ + \gamma_{c_{-i}}^{c_i} \log c_{-it} + \gamma_{h_1}^{c_i} \log h_{1t} + \gamma_{h_2}^{c_i} \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\gamma}^{\boldsymbol{c_i}}{}_x + \varepsilon_t^{c_i}, \quad i \in \{1, 2\}. \end{aligned} \tag{7}$$

This formulation allows for the analysis of various interdependencies within the household model, reflecting the relationships between wages, labor supply, commuting, and household expenditure decisions.[6] However, this analysis is limited to cross-sectional results. The focus of the static, reduced form setting is on the cross-sectional correlation between variables, net of observable factors, at a point in time. Such an approach provides a simple and clear picture of how variables correlate, but struggles with identifying causal relationships, and overlooks changes over time. In other words, equation (7) cannot capture how commuting respond to changes of other variables. To do so, we now move to the estimating equations in a life cycle setting.

Life cycle setting In the dynamic, quasi-reduced form setting, the estimating equations for spouses' commuting times are, assembling (6) and the modeling choices:[7]

$$\begin{aligned} \Delta \log c_{it} = c_{it-1}^{-1} \times \Big\{ & \gamma_0^{c_i} + \gamma_y^{c_i} \log y_{t-1} + \gamma_{\Delta y}^{c_i} \Delta \log y_t + \gamma_{\Delta a}^{c_i} \log a_{t-1} + \gamma_{\Delta a}^{c_i} \Delta \log a_t \\ & + \eta_i \Delta \log w_{it} \\ & + \gamma_H^{c_i} H_{t-1} \Delta \log H_t + \gamma_q^{c_i} q_{t-1} \Delta \log q_t + \gamma_{c_{-i}}^{c_i} c_{-it-1} \Delta \log c_{-it} \\ & + \gamma_{h_1}^{c_i} h_{1t-1} \Delta \log h_{1t} + \gamma_{h_2}^{c_i} h_{2t-1} \Delta \log h_{2t} + \boldsymbol{x}_{it}^{'} \boldsymbol{\gamma}_x^{c_i} \Big\} + \varepsilon_t^{c_i}, \\ & i \in \{1, 2\}, \ -i \neq i, \end{aligned} \tag{8}$$

Deriving equations in a life cycle setting provides additional insights to the static frame-

[6] Appendix B shows estimating equations for expenditures and work hours.

[7] Appendix B shows estimating equations for housing expenditure, consumption, and spouses' market work hours.

work. The life cycle approach focuses on how the growth of a variable from one time period to the next affects the fluctuation of another variable, i.e., on how variables evolve and react to changes of other variables. Thus, although static settings are often simpler and easier to develop, dynamic and life cycle analyses capture crucial additional dimensions of household behaviors ignored by the former approach (Chiappori and Mazzocco, 2017).

Coefficients in equations (7) and (8) represent the various relationships between spouses' commuting times, on the one hand, and the remaining variables, on the other hand, in the static and the life cycle setting, respectively. First, coefficients η_i, $i \in \{1, 2\}$, indicate the potential correlation between wages and commuting times. We assume that coefficients η_i are fixed, i.e., homogeneous among workers.[8] On the other hand, the remaining coefficients (i.e., the γ's) represent the different relationships between household behaviors, and commuting times (i.e., complementarity or substitution relationships), and also the moderating effects of demographics.

2.3 Intuition

The model incorporates key elements of traditional commuting models, such as trade-offs between commuting and housing, or housing and earnings being related to commuting (Leigh, 1986; Ross and Zenou, 2008; Ruppert et al., 2009; Fu and Ross, 2013; Mulalic et al., 2014), along with essential elements of household behavior (Browning et al., 2014). We assume that commuting and market work hours produce disutility for workers (in line with the conclusions of Van Ommeren and Fosgerau, 2009), while consumption and housing generate utility. A standard budget constraint is also incorporated, hypothesizing that workers' commuting may enter into the budget constraint (e.g., workers may receive compensatory wages for longer commutes).

We then study household behavior through the intra temporal optimality conditions of the household program. Specifically, we apply a standard log-linearization and derive estimating equations for spouses' commuting times.[9] These equations are derived in both a

[8]We tried heterogeneity in terms of occupation and education level. However, baseline estimates did not provide significant results. As a consequence, we decided to leave this heterogeneity analysis for future research.

[9]In addition to the commuting equations, we also derive equations for hours, consumption, and housing, although our focus is on household commuting behaviors. We would expect positive income effects in consumption and hours equations, while also negative substitution effects in hours equations. Complementarities between consumption and hours are also expected, while how commuting should relate to other household behaviors is not clearly identified.

pure reduced form, static setting and under a quasi-reduced form dynamic scenario, allowing us to empirically analyze some relationships between observable household factors.

Firstly, we analyze how household decision variables relate to one another within the model. Specifically, we examine the correlation between housing expenditure, consumption, and both male and female market work hours on the one hand, and household commuting times on the other hand, net of household observables, and net of income and wealth effects.

Secondly, the commuting time equations enable us to assess whether one's commuting time is related to the commuting time of their spouse. The relationship between worker labor supply and commuting time has been explored by Gershenson (2013), Gutiérrez-i Puigarnau and van Ommeren (2015), and Farré et al. (2023). However, to the best of our knowledge, the relationship between spouses' commuting times has not yet been investigated within a household behavior model, considering spousal commuting behaviors, and other household outcomes.

Thirdly, the estimating equations on spouses' commuting times allow us to understand whether wages are related to commuting times, controlling for income and wealth effects on commuting, and for other household behaviors. This complements existing analyses on commuting and wages in different contexts. For instance, Ross and Zenou (2008) and Giménez-Nadal et al. (2018) investigate wages and commuting in an urban efficiency wage model, where leisure and shirking are substitutes; Ruppert et al. (2009) analyze the impact of wages on commuting in a search model; Fu and Ross (2013) study wages, agglomeration, and residential location; and Mulalic et al. (2014) explore how wages respond to changes in commuting driven by firm relocation in a quasi-natural experiment setting. Our contribution extends these analyses by exploring the relationship between commuting and wages within a household model, from both static and life cycle perspectives.

3 Data and strategy

3.1 Data

We use public data from the Panel Study of Income Dynamics (PSID) for the period 2011 to 2019, when commuting time data became available. Administered by the University of Michigan, the PSID was established in 1968 as an extensive, nationally representative survey of US families (PSID, 2021). It is a panel household survey that includes a wide range of information for members of the interviewed households, such as employment outcomes and income, alongside other relevant details. The PSID is retrospective, meaning all information collected in a given survey wave pertains to the previous calendar year.

The PSID underwent a significant expansion in 1997, enhancing its scope to encompass additional topics, including consumption. Concurrently, it transitioned to a biennial collection schedule. The survey began collecting data on individuals' commuting times in interviewed households from 2011 onwards. Hence, our focus is on the survey years from 2011 to 2019, corresponding to the availability of commuting information.

3.2 Sample requirements

For our analysis, we retain information from households comprised of married or unmarried spouses, namely a husband, $i = 1$, and a wife, $i = 2$ (Grossbard, 2014). We select only working couples, meaning both spouses participate in the labor market and report positive market work hours, wages, and commuting time (Blundell et al., 2016; Theloudis et al., 2025). Additionally, complete data on demographic and labor outcomes, as well as non-zero information on consumption, housing expenditure, and wealth, are required.

Since the estimating equations involve several variables defined in first differences, we include in our sample households that meet the aforementioned criteria and are followed for at least two consecutive periods. Given the biennial nature of the PSID over the analyzed period, the first difference of a given variable is defined as the value of that variable in a given period minus its value in the previous period (two calendar years earlier), consistent with the approach used in existing research (Blundell et al., 2016; Theloudis, 2021; Theloudis et al., 2025).

These criteria result in a sample of 1,183 distinct households (i.e., 1,183 husbands and 1,183 wives). On average, a household is observed for 3.40 periods, amounting to our sample consisting of 4,021 observations (households$\times$years). Due to the requirement for first difference calculations, some estimation samples are smaller (2,820 observations corresponding to the 1,183 households when equations involve variables in first difference).

3.3 Variables

The PSID allows us to define the necessary variables to estimate the main equations, including spouses' market work hours, commuting time, and wages; household housing and consumption expenditures; and household earnings and wealth. Furthermore, it includes extensive information on demographic details and other relevant characteristics of the members of the interviewed households.

Spouses' market work hours in the PSID are reported in hours per year. Commuting times are presented in minutes per day, denoting two-way commuting time, which we convert to hours per year for consistency.[10] Wages are computed as individual annual earnings divided by annual hours of work, thus providing a measure in dollars per hour. Household earnings represent the sum of the labor earnings of both spouses, while household wealth is constructed in the PSID as the value of household assets minus debt, plus the value of home equity.[11]

Regarding consumption, the PSID includes data on various items that we aggregate to define household expenditure. This excludes housing expenditure, which we define separately, and also health insurance, hospital bills, and vehicle repairs, due to inconsistent data series before and after 2013. Consequently, our consumption expenditure measure comprises expenditures on food (both inside and outside the home), children's expenses (school and childcare), vehicles (gas, parking, and insurance), public transport, health and drugs, and utilities (electricity and water).[12] Housing expenditure is calculated as the sum of rents or rental value, housing services, and home insurances.

The PSID also allows the definition of several variables capturing spouses' and household demographics. These include the ages and races of the spouses, their education level, household composition, the number of children, the age of the youngest child, and the state of residence. Education is categorized into four groups: individuals with a doctorate, university graduates, those who completed high school but did not graduate, and those who did not complete high school. Race is identified with a dummy variable indicating whether respondents self-report as white.

TTable 1 presents the summary statistics for key variables.[13] In our sample, the average working hours and wages of husbands and wives differ significantly. Husbands work approximately 2,206 hours per year, earning an hourly wage of \$35.64, while wives work around 1,798 hours annually, earning \$26.86 per hour. These figures align with the findings of previous research (e.g. Blundell et al., 2016).

[10] Commuting is defined from survey question "*On a typical day, how many minutes is your round trip commute to and from work?*"; we assume a year consists of 250 workdays. An alternative approach would consist in using commuting distances defined in terms of distances between workplace and residence neighborhoods or metropolitan areas, as in Kirchmaier et al. (2024), but the PSID does not include this information.

[11] All monetary amounts are expressed in 2018 dollars.

[12] We define expenditure following existing research using the PSID (Theloudis, 2021; Theloudis et al., 2025).

[13] Figures C.1, C.2, and C.3 in Appendix C show the distribution of the key variables; additional descriptives are shown in Table C.1.

Table 1: Summary statistics of key variables

Individual variables	Males ($i = 1$)		Females ($i = 2$)		Difference	
	Mean	St.Dev.	Mean	St.Dev.	Diff.	p value
Work hours (h_{it})	2,206	580.9	1,798	621.3	408.4	0.000
$\Delta \log h_{it}$	-0.001	0.379	0.016	0.546	-0.018	0.144
Hourly wage (w_{it})	35.64	28.00	26.86	21.33	8.772	0.000
$\Delta \log w_{it}$	0.050	0.431	0.040	0.421	0.010	0.382
Commuting (c_{it})	191.4	162.9	160.8	130.1	30.52	0.000
$\Delta \log c_{it}$	-0.007	0.790	0.007	0.799	-0.014	0.485
Household variables			Mean	St.Dev.		
Expenditure (q_t)			26.36	14.32		
$\Delta \log q_t$			0.020	0.356		
Housing exp. (H_t)			17.56	12.00		
$\Delta \log H_t$			0.053	0.306		
Family earnings (y_t)			124.9	76.86		
Wealth (a_t)			361.1	818.4		
Households×waves			4,021			
Households			1,183			

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes. Work hours and commuting time are measured in hours/year. Earnings, wealth, and expenditures are measured in \$1,000/year.

Regarding commuting times, there is a notable gender disparity. Husbands, on average, commute for about 191.4 hours yearly, equivalent to around 45.9 minutes each workday. In contrast, wives have an annual average of 160.8 commuting hours, or approximately 38.6 minutes per workday. This significant gender gap in commuting patterns is supported by the findings of several studies.[14] As for household variables, the data shows that the average household in our sample spends around \$26,360 annually on non-durable consumption and approximately \$17,560 on housing. Furthermore, households in the sample report an average annual income of \$124,900 and a total wealth of about \$361,100.

3.4 Econometric strategy

When estimating equations (7), or the dynamic equations (8), for $i \in \{1, 2\}$, several approaches are feasible. A straightforward estimation of each equation using OLS could recover

[14] Sandow (2008); Roberts et al. (2011); Dargay and Clark (2012); McQuaid and Chen (2012); Le Barbanchon et al. (2021); Giménez-Nadal et al. (2022).

the coefficients of interest. However, this method assumes independence among equations, which is not the case here. Furthermore, the error terms may be correlated. As a consequence, OLS estimates would potentially lead to biased and inconsistent estimates (Cameron and Trivedi, 2005).

As the equations are interdependent, an alternative approach involves simultaneous estimation. This method addresses the simultaneous determination of variables, and accounts for possible correlations between error terms, enhancing the reliability and consistency of the estimates (Cameron and Trivedi, 2022). We use GMM to estimate the full set of equations both in the static reduced form setting, and in the dynamic quasi-reduced form scenario.[15] In doing so, we use robust-cluster standard errors at the household level, to account for potential heteroskedasticity and correlation within clusters (Cameron and Miller, 2015).

An essential consideration in our approach is the endogeneity between wages and commuting. In traditional cross-sectional urban and job-search empirical analyses, these variables are treated as endogenous due to unobserved characteristics of workers and employers that relate to both wages and commuting (Manning, 2003; Ross and Zenou, 2008; Fu and Ross, 2013). For example, workers willing to commute longer might also pursue higher-paying jobs. This relationship is also considered endogenous because earnings influence residential location choices, such as preferences for urban or rural areas, or for residing in the outskirts or close to the city center (Mulalic et al., 2014). Thus, one could instrument commuting using worker unobservables (e.g., worker fixed effects in panel data), firm fixed effects, and residence location fixed effects.

However, here in the household context, commuting times are not right-hand-side variables, but rather dependent variables, and instead, wages are right-hand-side variables. As a consequence, we cannot follow the identification strategies often used in the literature on commuting from the urban perspective. Alternatively, we instrument wages using a Mincer-style equation (Blundell et al., 2016), including individuals' quarter of birth.[16] The intuition is as follows. Workers' quarter of birth can impact educational attainment due to school enrollment rules in the US, as children born in different quarters of the same year may start school at different ages. This can lead to variations in their schooling duration, which ultimately affects their human capital accumulation.[17] As a consequence, we assume the quarter

[15] We estimate simultaneously the consumption equation, the housing equation, the commuting equations, and the work hours equations.

[16] We compute Hansen J test p-values of 0.636 among husbands and 0.210 among wives, which suggests that the econometric model is not over identified.

[17] Angrist and Krueger (1991) proposed the quarter of birth as an instrument for schooling, as kids born later in the year attain more schooling than those born earlier, due to the differential exposure to compulsory schooling. Since then, several authors have used the quarter of birth as an instrument. See for instance

of birth has an impact on wages. On the other hand, the quarter of birth could be considered exogenous to commuting decisions. It is determined at birth and is unlikely to be correlated with unobserved factors that directly affect commuting (e.g., personal preferences or job location choices). As a consequence, we consider it a valid instrument under the assumption that quarter of birth only affects commuting through its impact on wages.

4 Results

4.1 Reduced form results

Table 2 shows the results of estimating (7) for husbands and wives. Columns (1) and (2) show GMM estimates without household fixed effects, whereas Columns (3) and (4) show similar estimates when we instrument wages, and Columns (5) and (6) show estimates including household fixed effects.[18] Estimates on the remaining household dependent variables, as well as results for the demographics, are shown in Appendix D.

The baseline results show that wages and commuting are strongly related in the cross-section. Specifically, results indicate that a 10% increase in wages relates to an increase in commuting times of about 2.52% among husbands, and 3.22% among wives. These coefficients are statistically significant at standard levels, in line with the literature on the relationship between wages and commuting time. Besides that, we cannot reject that these coefficients are similar at standard levels ($p = 0.311$). Estimates also shed light on the relationships between earnings, wealth, and other household behaviors on the one hand, and spouses' commuting time on the other hand. First, household earnings relate negatively to female commuting time, but their relation to male commuting time is not significant at standard levels. On the other hand, it is wealth which is found to be negatively related to the husband's commuting time, but not to the wife's, while non-durables consumption relates positively to the husband's commuting time. We also find strong and positive relationships between spouses' commuting times, which suggest complementarity or joint household decision-making. These findings align with theoretical expectations and underline the interconnected nature of spousal decisions. However, we remain agnostic regarding the potential channels that drive such complementarity, which would require a more involved, structural strategy.

recent analyses by Robertson (2011) and Rietveld and Webbink (2016). We build on this intuition to instrument the relationship between wages and commuting times.

[18]Estimates with household fixed effects exclude regressors that are constant within households, such as spouses' education and race.

Table 2: Reduced form results

	Baseline		IV		Household fixed effects	
Dep. var.: $\log c_{it}$ Variables	Males $i=1$	Females $i=2$	Males $i=1$	Females $i=2$	Males $i=1$	Females $i=2$
$\log w_{it}$	0.252***	0.322***	0.170*	0.111	0.020	0.029*
	(0.054)	(0.043)	(0.101)	(0.100)	(0.020)	(0.016)
$\log y_t$	-0.022	-0.168***	0.228***	0.032	-0.041	-0.075***
	(0.075)	(0.056)	(0.054)	(0.051)	(0.027)	(0.020)
$\log a_t$	-0.077***	-0.010	-0.082***	-0.013	-0.009	0.003
	(0.015)	(0.016)	(0.015)	(0.017)	(0.005)	(0.006)
$\log H_t$	0.008	0.041	0.006	0.056	0.026**	0.031**
	(0.040)	(0.038)	(0.040)	(0.039)	(0.012)	(0.013)
$\log q_t$	0.219***	0.065	0.206***	0.071	0.036*	0.039**
	(0.048)	(0.050)	(0.048)	(0.051)	(0.019)	(0.019)
$\log c_{-it}$	0.316***	0.331***	0.313***	0.320***	0.057***	0.052***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.010)	(0.013)
$\log h_{1t}$	-0.014	0.009	-0.104**	-0.078*	0.004	-0.007
	(0.051)	(0.047)	(0.051)	(0.046)	(0.023)	(0.017)
$\log h_{2t}$	-0.046	0.073**	-0.114***	0.065**	-0.007	0.015
	(0.031)	(0.030)	(0.029)	(0.030)	(0.013)	(0.014)
Constant	2.882***	2.782***	3.301***	3.346***	-0.271	-0.254
	(0.473)	(0.482)	(0.514)	(0.525)	(0.215)	(0.202)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Occupation f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Region f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Household f.e.	No	No	No	No	Yes	Yes
Observations	4,021	4,021	4,021	4,021	4,021	4,021

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes. Robust standard errors in parentheses, clustered at the household level. *** significant at the 1%; ** significant at the 5%; * significant at the 10%.

Columns (3) and (4) show the main estimates when we instrument the log of wages. First, the relationship between husband wage and husband commuting time decreases, suggesting that a 10% increase in wages relates to an increase in the commuting time of about 1.70%, with the coefficient being marginally significant. Among wives, the correlation between wages and commuting times is not significant at standard levels, partially driven by the large standard error.[19] Besides this, the remaining coefficients are quite similar than those estimated in Columns (1) and (2). Specifically, we find that earnings relate positively to husband commuting time, while wealth shows a negative coefficient. Estimates for expenditures and spousal commuting times are similar, while we estimate negative relationships between husband commuting, and husband and wife market work hours, a negative correlation between wife commuting and husband hours of work, and a positive correlation between wife commuting and market work hours.

Finally, Columns (5) and (6) show estimates controlling for household fixed effects, to exploit the panel structure of the data and net out household unobservables. First of all, once we net out household unobservables, the conditional correlation between commuting time and wages decreases significantly ($p < 0.001$), becoming not statistically significant among husbands, and marginally significant at the 10% among wives. In other words, results suggest that the cross-sectional correlation between wages and commuting time could be mostly explained by household unobserved characteristics. In addition to this, we estimate a negative correlation between family earnings and wives' but not husbands' commuting time; positive correlations between household expenditures on housing and on non-durables, and commuting; and positive correlations between spouses' commuting time, which again indicate some form of complementarity between the commuting times of the husband and the wife. However, the relationship between spouses' hours of work and commuting times is not significant at standard levels, suggesting that said correlations could be explained by household unobserved heterogeneity.

[19] This suggests that the cross-sectional correlations estimated in Columns (1) and (2), which capture the causal and the spurious components of the wages-commuting relationship, are potentially biased upwards. When we instrument wages we isolate the variation that is driven by the Mincer equation including the quarter of birth, which is weaker but closer to the causal relationship with commuting. However, coefficients associated to wages are not statistically significant, as standard errors are relatively large, which may be indicative of a weak instrumentation (the F-statistic of the first stage is about 5.1 among husbands and 4.3 among wives). This points that our IV estimates would still be biased upwards (Bound et al., 1995).

4.2 Life cycle results

Estimates of the life cycle equation (8) are shown in Table 3, for husbands and wives. Columns (1) and (2) show GMM estimates without household fixed effects, whereas Columns (3) and (4) show similar estimates when we instrument wages. Estimates on the remaining household dependent variables, as well as results for the demographics, are shown in Appendix D.

Overall, the results are quite robust regardless of whether we instrument or do not instrument wages. First of all, estimates indicate that changes in wages do not relate to changes in commuting times, for neither husbands nor wives, as the coefficients are not statistically significant at standard levels. This result is partially in line with the reduced form results including household fixed effects. Again, it suggests that it is household and/or worker unobservables which relate to commuting from a life cycle perspective, but wages do not relate to commuting once such unobservables are captured, and changes in wages do not relate to changes in commuting times over time.

Conversely, the results suggest the existence of a strong and highly significant income effect, driven by past family earnings. Both husbands and wives in households with high earnings report increased commuting times, although changes in family earnings do not relate to changes in commuting time, and only relate marginally to changes in male commuting, exhibiting a positive correlation that is statistically significant only at the 10% level. Similarly, changes in wealth are not related to the growth rate of spouses' commuting, although past wealth does relate negatively to both husband and wife changes in commuting time.

As for how changes in other household behavior relate to changes in commuting times, estimates show that the growth rate of housing expenditure relates to decreases in commuting time only among husbands (and only when wages are not instrumented), but the similar coefficient for wives is not significant at standard levels. Oppositely, changes in the consumption of durables are positively related to changes in male commuting time, reflecting some form of complementarity between male commuting time and household expenditure. The similar coefficient for wives is positive and statistically significant only at the 10%, and of smaller magnitude, suggesting that husbands' commuting time is more sensitive to consumption responses than the commuting time of wives. Regarding spousal commuting time, and spouses' labor supplies, all the associated coefficients are not statistically significant at standard levels. As a consequence, we do not find evidence supporting dynamic correlations between spouses' commuting times, or between spouses' labor supplies and commuting times. In other words, the dynamic analysis does not provide support for a significant relationship between spousal commuting growth rates, and this stability might reflect the initial equilibrium established in static cross-sectional decisions.

Table 3: Estimates of first difference equations

	Baseline		IV	
Dep. var.: $\Delta \log c_{it}$ Variables	Males $i = 1$	Females $i = 2$	Males $i = 1$	Females $i = 2$
$\Delta \log w_{it}$	-3.595	1.244	-4.033	7.061
	(2.777)	(2.302)	(7.114)	(7.507)
$\log y_{t-1}$	8.566***	6.290***	8.273***	6.053***
	(1.478)	(1.422)	(1.494)	(1.496)
$\Delta \log y_t$	7.810*	-1.153	3.955	-0.714
	(4.733)	(2.728)	(3.206)	(2.062)
$\log a_{t-1}$	-1.219*	-1.643**	-1.257*	-1.631**
	(0.721)	(0.664)	(0.722)	(0.648)
$\Delta \log a_t$	0.381	-0.870	0.311	-0.918
	(0.984)	(0.947)	(0.951)	(0.940)
$\Delta \log H_t$	-0.220*	0.311	-0.196	0.327
	(0.121)	(0.223)	(0.125)	(0.227)
$\Delta \log q_t$	0.207***	0.097	0.204***	0.106*
	(0.072)	(0.059)	(0.073)	(0.060)
$\Delta \log c_{-it}$	0.004	0.003	0.005	0.003
	(0.010)	(0.003)	(0.010)	(0.003)
$\Delta \log h_{1t}$	-0.002	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta \log h_{2t}$	-0.001	0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Constant	-0.210***	-0.212***	-0.209***	-0.210***
	(0.016)	(0.018)	(0.016)	(0.018)
Demographics	Yes	Yes	Yes	Yes
Occupation f.e.	Yes	Yes	Yes	Yes
Region f.e.	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes. Robust standard errors in parentheses, clustered at the household level. *** significant at the 1%; ** significant at the 5%; * significant at the 10%.

5 Discussion

The cross-sectional correlations between wages and commuting time, estimated in the household reduced form, static analysis, are in line with existing research on commuting behavior. Specifically, we report an elasticity between wages and commuting of around 0.32 among females and 0.25 among males in our sample. These magnitudes suggest that a 10% increase in female (male) wages relates to increases in commuting time of about 3.2% (2.5%). In other words, an average increase of about \$2.7 and \$3.6 per hour in female and male wage, respectively, relates to an increase of about 5.1 and 4.8 female and male commuting hours per year. This indicates that each additional hour of commuting is valued at \$0.53 for females, and at \$0.75 for males.

These estimates are in line with several existing analyses. Leigh (1986) report similar results for white US workers, although not in a household context and focusing only on male workers. In the Netherlands, Van Ommeren et al. (1999) estimate a willingness to pay about \$0.25 for each commuting kilometer , focusing on commuting distance rather than on commuting time, close to an elasticity of 0.4.[20] Renkow and Hoover (2000) also find a positive and significant correlation between wages and commuting in the US, although the magnitude is not readily comparable due to their use of aggregate flows at the county level.

More recently, Ross and Zenou (2008) found a positive correlation between commuting time and wages in the US among workers in supervised occupations, in an urban efficiency wage setting, and Giménez-Nadal et al. (2018) concluded similarly using US time use surveys. Van Ommeren and Fosgerau (2009) found that the disutility of one hour of commuting is twice as large as the net wage of a worker in the Netherlands. Ruppert et al. (2009) found that a one hour increase in commuting relates to an increase of 29% in wages in France. Le Barbanchon et al. (2021) use French administrative data to quantify the value of commute time at 80% of wages for males, and 98% among females. Also using French data, Aboulkacem and Nedoncelle (2022) find that wage increases translate into increased commuting distance. Other authors finding positive correlations between wages and commuting in different contexts include Green et al. (2019), Dauth and Haller (2020), and Borghorst et al. (2021).

Despite that, another important result is that our reduced form static baseline estimates diverge from estimates instrumenting wages and accounting for endogeneity, and also from estimates in which we net out unobserved household heterogeneity by including household

[20] Previous analyses also found a marginal willingness to pay between 0.25 and 0.5 of the wage rate, in line with the elasticity between wages and commutes we estimate in our reduced form, static analysis; see Small and Song (1992) for a review.

fixed effects. Specifically, once we instrument wages or include household fixed effects, the correlation between wages and commutes either decreases significantly, or becomes not statistically significant. This would indicate that estimates not accounting for endogeneity could be biased upwards, and that the positive correlation found between commuting and wages may be largely driven by unobserved worker characteristics. As a consequence, correlational studies on wages and commuting should be considered cautiously, and further research should dive deeper into said correlation, e.g., analyzing potential heterogeneity, or studying endogeneity biases.

We also contribute to the growing literature on the interrelations between commuting and other behaviors in the household. In doing so, we analyze the relationship between commuting and spouses labor supplies (e.g. Gutiérrez-i Puigarnau and van Ommeren, 2010, 2015). We find gender disparities as we report negative correlations between husband commuting time and male and female hours of work, and a positive correlation between wives' commuting and their own hours of work. Our results suggest that such correlations are partially driven by household unobserved heterogeneity, as they become not statistically significant at standard levels once we account for household fixed effects. Estimates also indicate positive correlations between expenditures (both in non durables and in housing) on one hand, and spouses' commuting times on the other hand. These positive correlations are in line with the key underlying idea of a trade-off between commuting and housing, as households residing in better (potentially more expensive) neighborhoods with better amenities must face longer commutes, as such residences are typically in the city outskirts.

We consistently estimate a positive correlation between spouses' commuting times, which is partially but not completely driven by unobserved factors. Then again, this complementarity is in line with the trade-off between commuting and housing, as it would indicate that in households residing further away from business districts, both spouses need to commute for longer times. There are alternative explanations for this positive correlation. For instance, it may be that longer commutes of a given spouse require his/her use of the family vehicle, relegating the other spouse to alternative (perhaps more time consuming) commuting modes. Household responsibilities may also explain the correlation, as longer commutes of a given spouse could lead to increased chores or childcare responsibilities of the other spouse, who needs to adapt his/her commuting trip (potentially increasing commuting times) to do these responsibilities. Unfortunately, a deeper analysis of these channels would require detailed information on commuting modes, commuting directions, or secondary activities done while commuting, which is not provided in the PSID.

In the second part of our empirical analysis, we adopt a life cycle perspective and estimate first difference equations that allow us to study how changes in wages relate to changes in commuting time within households. This perspective resembles previous analyses by Gutiérrez-i Puigarnau and van Ommeren (2010) and Mulalic et al. (2014). However, Gutiérrez-i Puigarnau and van Ommeren (2010) focuses on labor supply, and Mulalic et al. (2014) on wages as key dependent variables. As a consequence, our results – based on a household context in which commuting times are endogenous decisions and wages are right-hand-side variables – are not readily comparable to theirs. Furthermore, our life cycle results suggest that the correlation between changes in wages and changes in commuting is not statistically significant at standard levels, in line with Mulalic et al. (2014) who conclude that the impact of wages on commutes is negligible in the short-run and only moderate in the longer run. Furthermore, the stability of commuting times over time, as reflected in our life cycle results, suggests that high moving costs and the complexities of changing jobs may act as significant barriers to adjustments in commuting patterns.

Regarding how other household characteristics and behaviors relate to changes in spouses' commuting times, our life cycle estimates indicate that family income and wealth level relate to the evolution of spouses' commuting times, although changes in wealth and changes in family earnings are not significant. This would indicate that past changes relate to current commuting behaviors, in line with conclusions by Mulalic et al. (2014). In addition to this, our results also indicate that most household behaviors do not relate significantly to changes in commuting, a result perhaps driven by the stability of commuting over time. This would indicate that commuting is a steady process for households, and once spouses set a given commuting time that satisfies them, such commuting time remains mostly unchanged under changes of other behaviors.

The divergence between estimates in the reduced form analysis and estimates in the life cycle setting has potential implications. Specifically, the results suggests that choices regarding the measure of the variables of interest are important, and results reflecting differences in the cross-section (i.e., among workers) may differ from results over time. Besides, this is important not only in terms of wages and commuting, but also in terms of the different relationships among the household outcomes analyzed, namely consumption of non-durables, housing expenditures, market work hours, and commuting. Our static analysis shows significant complementarities between commuting and consumption, and between spouses' commuting times, and also significant relationships between commuting and work hours, most of which survive after controlling for household fixed effects. Contrarily, the equations in first difference suggest that only changes in consumption relate to changes in household commuting times.

A potential explanation for these results is that workers choose their commuting time reflecting cross-sectional differences in terms of observables and non observables in the cross-section, as described in Table 2. However, once some initial decision regarding commuting times is fixed, they do not meaningfully change over time responding to changes in wages, spousal commuting, or work hours, according to estimates in Table 3. Despite that, we do find significant correlations in the life cycle analysis, especially among earnings, wealth, consumption, and commuting times. The channels through which these correlations emerge remain unclear, and a fully specified (i.e. fully structural) and more involved household model should shed light on the potential channels that drive the correlations reported by our analysis.

6 Conclusions

This paper explores the interconnected relationships of commuting, wages, labor supply, and consumption within a household model, particularly focusing on two-member households. We first develop a household model incorporating spouses' commuting as a choice variable, and assuming that commuting may affect household earnings. We then derive the optimality conditions across both static and life cycle frameworks. Using data from the PSID for the period 2011-2019, when commuting is observed, the empirical analysis reveals intricate relationships between commuting times, wages, and various household and economic factors.

We first report a positive cross-sectional correlation between spouses' wages and commuting times, as a 10% increase in wages is associated with approximately 2.5% to 3.2% increase in commuting time, in line with existing research on commuting relying on urban and job-search models. However, this correlation decreases significantly once we account for endogeneity between commuting and wages, and seems to disappear when we exploit the longitudinal dimension of the data and account for unobserved heterogeneity or estimate first difference equations. These results indicate that the positive cross-sectional correlation found by existing research might be largely driven by unobserved household characteristics rather than a direct effect of wages on commuting.

The results also highlight relationships between household earnings and wealth and spouses' commuting, especially in the life cycle analysis, as the former relates to increased commuting times, while the latter relates negatively to changes in the commuting times of husbands and wives. Furthermore, the correlations estimated between spouses' commuting, and also between commuting, on the one hand, and consumption and market work hours, on the other hand, seem to be especially relevant in the cross-section, while the dynamics of spouses' commuting tend to be quite stable and unrelated to changes in other household behaviors.

A key point in our empirical analysis stems from potential endogeneity between commuting time and wages. While we address this issue using an instrumental variable approach based on a Mincer-style equation incorporating individuals' quarter of birth, unobserved factors such as job preferences, workplace flexibility, or unmeasured productivity shocks could still influence both wages and commuting choices. If these omitted variables are correlated with our key regressors, our estimates may be biased, potentially overstating or understating the causal effect of wages on commuting. Additionally, while our longitudinal approach helps mitigate concerns related to unobserved heterogeneity, measurement error in self-reported commuting times or wages could introduce attenuation bias, affecting the precision of our estimates.

Another limitation arises from sample selection. Our analysis is restricted to dual-earner households, which may not be representative of the broader labor market. Households with only one employed spouse or those with non-standard work arrangements (e.g., remote work or flexible schedules) may exhibit different commuting-wage dynamics. Furthermore, while the PSID provides rich longitudinal data, the sample size remains relatively small, particularly for estimating dynamic household behaviors. As a result, external validity could be limited, especially when generalizing our findings to different labor market contexts or institutional settings.

Statements and Declarations

Funding: This work was supported by the Government of Aragón [Project S32_23R, Program FSE Aragón 2014-2020].

Financial interests: The authors declare they have no financial interests.

Non-financial interests: none.

References

Aboulkacem, E.-M. and C. Nedoncelle (2022). Wage variations and commuting distance. *Journal of Economic Geography 22*(5), 1097–1123.

Albouy, D. and B. Lue (2015). Driving to opportunity: Local rents, wages, commuting, and sub-metropolitan quality of life. *Journal of Urban Economics 89*, 74–92.

Alonso, W. (1964). *Location and land use: Toward a general theory of land rent*. Harvard university press.

Anderson, K. (2012). The effect of economic autonomy on women's labor force participation and mobility. *American Economic Review 102*(3), 983–1008.

Angrist, J. D. and A. B. Krueger (1991). Does compulsory school attendance affect schooling and earnings? *Quarterly Journal of Economics 106*(4), 979–1014.

Becker, G. S. (1957). *The Economics of Discrimination*. University of Chicago Press.

Bertrand, M., C. Goldin, and L. F. Katz (2010). Dynamics of the gender gap for young professionals in the corporate and financial sectors. *American Economic Journal: Applied Economics 2*(3), 228–255.

Blau, F. D. and L. M. Kahn (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature 55*(3), 789–865.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016). Consumption inequality and family labor supply. *American Economic Review 106*(2), 387–435.

Borghorst, M., I. Mulalic, and J. Van Ommeren (2021). Commuting, children and the gender wage gap. *Tinbergen Institute Discussion Paper TI 2021-089/VIII*.

Bound, J., D. A. Jaeger, and R. M. Baker (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American statistical association 90*(430), 443–450.

Browning, M., P.-A. Chiappori, and Y. Weiss (2014). *Economics of the Family*. Cambridge University Press.

Cameron, A. and P. Trivedi (2005). *Microeconometrics Methods and Applications*. Cambridge University Press.

Cameron, A. and P. Trivedi (2022). *Microeconometrics Using Stata, Second Edition*. Stata-Corp LP.

Cameron, A. C. and D. L. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources 50*(2), 317–372.

Casado-Díaz, J. M., R. Simón-Albert, and H. Simón (2023). Gender differences in commuting: New evidence from Spain. *Social Indicators Research 169*(3), 907–941.

Chandra, A. and J. Thompson (2000). Wages and commuting: Evidence from the united states. *Journal of Urban Economics 48*(1), 15–34.

Chiappori, P.-A., B. Fortin, and G. Lacroix (2002). Marriage market, divorce legislation, and household labor supply. *Journal of Political Economy 110*(1), 37–72.

Chiappori, P.-A. and M. Mazzocco (2017). Static and intertemporal household decisions. *Journal of Economic Literature 55*(3), 985–1045.

Cogan, J. F. (1981). Fixed costs and labor supply. *Econometrica 49*(4), 945–963.

Cohen, P. N. (2013). *Women's Work and Economic Mobility: The Long-Term Impact of Employment on Women's Life Chances*. Princeton University Press.

Dargay, J. M. and S. Clark (2012). The determinants of long distance travel in great britain. *Transportation Research Part A: Policy and Practice 46*(3), 576–587.

Dauth, W., S. Findeisen, E. Moretti, and J. Suedekum (2022). Matching in cities. *Journal of the European Economic Association 20*.

Dauth, W. and P. Haller (2020). Is there loss aversion in the trade-off between wages and commuting distances? *Regional Science and Urban Economics 83*, 103527.

De Palma, A., R. Lindsey, and N. Picard (2015). Trip-timing decisions and congestion with household scheduling preferences. *Economics of Transportation 4*(1-2), 118–131.

Dube, J.-P. and P. Chalavan (2015). The economics of commuting and wage premiums. *Journal of Transport Economics and Policy 49*(2), 127–146.

Ehrenberg, R. G. and R. S. Smith (2003). *Modern Labor Economics: Theory and Public Policy* (8th ed.). Addison-Wesley.

Farré, L., J. Jofre-Monseny, and J. Torrecillas (2023). Commuting time and the gender gap in labor market participation. *Journal of Economic Geography 23*(4), 847–870.

Folbre, N. (2001). *The Invisible Heart: Economics and Family Values*. The New Press.

Fortin, N. M. (2005). Gender role attitudes and the labour market outcomes of women and men. *Canadian Journal of Economics 38*(2), 347–363.

Fortin, N. M. (2015). The gender wage gap among young adults in the united states: The importance of labor market attachment. *Economica 82*, 89–104.

Fu, S. and S. L. Ross (2013). Wage premia in employment clusters: How important is worker heterogeneity? *Journal of Labor Economics 31*(2), 271–304.

Gershenson, S. (2013). The causal effect of commute time on labor supply: Evidence from a natural experiment involving substitute teachers. *Transportation Research Part A: Policy and Practice 54*, 127–140.

Giménez-Nadal, J. I., J. A. Molina, and J. Velilla (2018). Spatial distribution of us employment in an urban efficiency wage setting. *Journal of Regional Science 58*(1), 141–158.

Giménez-Nadal, J. I., J. A. Molina, and J. Velilla (2022). Trends in commuting time of european workers: A cross-country analysis. *Transport Policy 116*, 327–342.

Glaeser, E. L. and M. E. Kahn (2004). Sprawl and urban growth. *American Economic Review 94*(2), 482–488.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review 104*(4), 1091–1119.

Green, D. A., R. Morissette, B. M. Sand, and I. Snoddy (2019). Economy-wide spillovers from booms: Long-distance commuting and the spread of wage effects. *Journal of Labor Economics 37*(S2), S643–S687.

Grossbard, S. (2014). *The marriage motive: A price theory of marriage: How marriage markets affect employment, consumption, and savings*. Springer.

Gutiérrez-i Puigarnau, E. and J. N. van Ommeren (2010). Labour supply and commuting. *Journal of Urban Economics 68*(1), 82–89.

Gutiérrez-i Puigarnau, E. and J. N. van Ommeren (2015). Commuting and labour supply revisited. *Urban Studies 52*(14), 2551–2563.

Hansen, W. (2005). Wage-commuting trade-offs in the united states. *Regional Science and Urban Economics 35*(3), 309–331.

Hsieh, C. T., E. Hurst, C. I. Jones, and P. J. Klenow (2019). The allocation of talent and u.s. economic growth. *Econometrica 87*(5), 1439–1474.

Huai, Y., H. K. Lo, and K. F. Ng (2021). Monocentric versus polycentric urban structure: Case study in hong kong. *Transportation Research Part A: Policy and Practice 151*, 99–118.

Illing, H., J. F. Schmieder, and S. Trenkle (2024). The gender gap in earnings losses after job displacement. *Journal of the European Economic Association 22*.

Jacob, N., L. Munford, N. Rice, and J. Roberts (2019). The disutility of commuting? the effect of gender and local labor markets. *Regional Science and Urban Economics 77*, 264–275.

Kirchmaier, T., M. Langella, and A. Manning (2024). Commuting for crime. *Economic Journal 134*(659), 1173–1198.

Kleven, Henrik, L. C. and J. E. Søgaard (2019). Children and gender inequality: Evidence from denmark. *American Economic Journal: Applied Economics 11*(4), 181–209.

Le Barbanchon, T., R. Rathelot, and A. Roulet (2021). Gender differences in job search: Trading off commute against wage. *Quarterly Journal of Economics 136*(1), 381–426.

Leigh, J. P. (1986). Are compensating wages paid for time spent commuting? *Applied Economics 18*(11), 1203–1214.

Liotta, C., V. Viguié, and Q. Lepetit (2022). Testing the monocentric standard urban model in a global sample of cities. *Regional Science and Urban Economics 97*, 103832.

Lise, J. and K. Yamada (2019). Household sharing and commitment: Evidence from panel data on individual expenditures and time use. *Review of Economic Studies 86*(5), 2184–2219.

Manning, A. (2003). The real thin theory: Monopsony in modern labour markets. *Labour Economics 10*(2), 105–131.

Mazzocco, M. (2007). Household intertemporal behaviour: A collective characterization and a test of commitment. *Review of Economic Studies 74*(3), 857–895.

McQuaid, R. W. and T. Chen (2012). Commuting times–the role of gender, children and part-time work. *Research in Transportation Economics 34*(1), 66–73.

Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *American Economic Review 57*(2), 197–210.

Mulalic, I., J. N. Van Ommeren, and N. Pilegaard (2014). Wages and commuting: Quasi-natural experiments' evidence from firms that relocate. *Economic Journal 124*(579), 1086–1105.

Neto, R. S., G. Duarte, and A. Páez (2015). Gender and commuting time in são paulo metropolitan region. *Urban Studies 52*(2), 298–313.

Olivetti, C., J. Pan, and B. Petrongolo (2024). The evolution of gender in the labor market. In *Handbook of Labor Economics*, Volume 5, pp. 619–677.

Olivetti, C. and B. Petrongolo (2016). The evolution of gender gaps in industrialized countries. *Annual Review of Economics 8*, 405–434.

Petrongolo, B. and M. Ronchi (2020). The effect of commuting time on gender wage gaps: Evidence from italy. *Review of Economics and Statistics 102*(5), 855–869.

Polachek, S. W. (1981). Occupational segregation and earnings differences: A survey of the evidence. *Research in Labor Economics 4*, 1–28.

PSID (2021). Panel study of income dynamics, public use dataset. Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI (2021).

Renkow, M. and D. Hoover (2000). Commuting, migration, and rural-urban population dynamics. *Journal of Regional Science 40*(2), 261–287.

Rietveld, C. A. and D. Webbink (2016). On the genetic bias of the quarter of birth instrument. *Economics & Human Biology 21*, 137–146.

Roberts, J., R. Hodgson, and P. Dolan (2011). "It's driving her mad": Gender differences in the effects of commuting on psychological health. *Journal of Health Economics 30*(5), 1064–1076.

Robertson, E. (2011). The effects of quarter of birth on academic outcomes at the elementary school level. *Economics of Education Review 30*(2), 300–311.

Ross, S. L. and Y. Zenou (2008). Are shirking and leisure substitutable? An empirical test of efficiency wages based on urban economic theory. *Regional Science and Urban Economics 38*(5), 498–517.

Ruppert, P., E. Stancanelli, and E. Wasmer (2009). Commuting, wages and bargaining power. *Annals of Economics and Statistics 95/96*, 201–220.

Sandow, E. (2008). Commuting behaviour in sparsely populated areas: Evidence from northern Sweden. *Journal of Transport Geography 16*(1), 14–27.

Severen, C. (2023). Commuting, labor, and housing market effects of mass transportation: Welfare and identification. *Review of Economics and Statistics 105*(5), 1073–1091.

Small, K. A. and S. Song (1992). "Wasteful" commuting: a resolution. *Journal of Political Economy 100*(4), 888–898.

Theloudis, A. (2021). Consumption inequality across heterogeneous families. *European Economic Review 136*, 103765.

Theloudis, A., J. Velilla, P.-A. Chiappori, J. I. Gimenez-Nadal, and J. A. Molina (2025). Commitment and the dynamics of household labor supply. *Economic Journal 135*(665), 354–386.

Van Ommeren, J. and M. Fosgerau (2009). Workers' marginal costs of commuting. *Journal of Urban Economics 65*(1), 38–47.

Van Ommeren, J., P. Rietveld, and P. Nijkamp (1999). Job moving, residential moving, and commuting: a search perspective. *Journal of Urban economics 46*(2), 230–253.

Van Ommeren, J., G. J. Van Den Berg, and C. Gorter (2000). Estimating the marginal willingness to pay for commuting. *Journal of Regional Science 40*(3), 541–563.

Van Ommeren, J. N. and J. W. van der Straaten (2008). The effect of search imperfections on commuting behaviour: Evidence from employed and self-employed workers. *Regional Science and Urban Economics 38*(2), 127–147.

Appendices

A Log-linearization in the life cycle setting

Here we show details on the log-linearization of the optimality conditions of the life cycle approach. For simplicity, we focus on husband commuting times, c_{1t}. The same applies analogously to the remaining set of variables (i.e., H_t, q_t, c_{2t}, h_{1t} and h_{2t}).

The first order condition on husband commuting time is given by $-\tilde{U}_{[c_1]} \exp\left(-\boldsymbol{x}_t' \xi_t^{c_1}\right) = \lambda_t \eta_{1t} w_{1t}$, which can be expressed taking logs and first difference as: $\Delta \log(-\tilde{U}_{[c_1]}) = \Delta \boldsymbol{x}_t' \xi_t^{c_1} + \Delta \log \lambda_t + \Delta \log(\eta_{1t} w_{1t})$, where $\tilde{c}_{1t} = c_{1t} e^{-\boldsymbol{x}_{it}' \xi_{it}^{c_{1t}}}$. Then, a Taylor approximation of $\log(-\tilde{U}_{[c_1]})$, around its arguments one period ago (Blundell et al., 2016) and using that $\Delta x_t \approx x_{t-1} \Delta \log x_t$ for small changes in x, yields:

$$
\begin{aligned}
\log\left(-\tilde{U}_{[c_1]}\left(\tilde{H}_t, \tilde{q}_t, \tilde{c}_{1t}, \tilde{c}_{2t}, \tilde{h}_{1t}, \tilde{h}_{2t}\right)\right) = {} & \log\left(-\tilde{U}_{[c_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)\right) \\
& + \frac{\tilde{U}_{[c_1,H]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)}{\tilde{U}_{[c_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)} \tilde{H}_{t-1} \Delta \log H_t \\
& + \frac{\tilde{U}_{[c_1,q]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)}{\tilde{U}_{[c_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)} \tilde{q}_{t-1} \Delta \log q_t \\
& + \frac{\tilde{U}_{[c_1,c_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)}{\tilde{U}_{[c_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)} \tilde{c}_{1t-1} \Delta \log c_{1t} \\
& + \frac{\tilde{U}_{[c_1,c_2]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)}{\tilde{U}_{[c_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)} \tilde{c}_{2t-1} \Delta \log c_{2t} \\
& + \frac{\tilde{U}_{[c_1,h_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)}{\tilde{U}_{[c_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)} \tilde{h}_{1t-1} \Delta \log h_{1t} \\
& + \frac{\tilde{U}_{[c_1,h_2]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)}{\tilde{U}_{[c_1]}\left(\tilde{H}_{t-1}, \tilde{q}_{t-1}, \tilde{c}_{1t-1}, \tilde{c}_{2t-1}, \tilde{h}_{1t-1}, \tilde{h}_{2t-1}\right)} \tilde{h}_{2t-1} \Delta \log h_{2t}.
\end{aligned}
$$

This equation can be rewritten as:

$$\Delta \log\left(-\tilde{U}_{[c_1]}\right) = \phi_H^{c_1} H_{t-1}\Delta \log H_t + \phi_q^{c_1} q_{t-1}\Delta \log q_t + \phi_{c_1}^{c_1} c_{1t-1}\Delta \log c_{1t} \\ + \phi_{c_2}^{c_1} c_{2t-1}\Delta \log c_{2t} + \phi_{h_1}^{c_1} h_{1t-1}\Delta \log h_{1t} + \phi_{h_2}^{c_1} h_{2t-1}\Delta \log h_{2t},$$

where $\phi_x^{c_1} = \dfrac{\tilde{U}_{[c_1,x]}}{\tilde{U}_{[c_1]}} \exp(-\Delta \boldsymbol{x}_t' \xi_t^{c_1})$, for each variable x of interest. Therefore, once the modeling choices on $\Delta \log \lambda_t$ and $\Delta \log(\eta_{1t} w_{1t})$ are applied, the equation characterizing husband optimal commuting behavior can be expressed as:

$$\begin{aligned}
\Delta \log c_{1t} \approx c_{1t-1} \times \Big\{ & + \underbrace{(\phi_{c_1}^{c_1})^{-1} \xi_t^{c_1'}}_{=\boldsymbol{\gamma}_x^{c_1}} \Delta \boldsymbol{x}_t \\
& + \underbrace{(\phi_{c_1}^{c_1})^{-1} \zeta_1}_{=\gamma_y^{c_1}} \log y_{t-1} + \underbrace{(\phi_{c_1}^{c_1})^{-1} \zeta_2}_{=\gamma_{\Delta y}^{c_1}} \Delta \log y_t \\
& + \underbrace{(\phi_{c_1}^{c_1})^{-1} \zeta_3}_{=\gamma_a^{c_1}} \log a_{t-1} + \underbrace{(\phi_{c_1}^{c_1})^{-1} \zeta_4}_{=\gamma_{\Delta a}^{c_1}} \Delta \log a_t \\
& + \underbrace{(\phi_{c_1}^{c_1})^{-1} \eta_{1t}}_{\equiv \eta_1} \Delta \log w_{1t} \\
& \underbrace{-(\phi_{c_1}^{c_1})^{-1} \phi_H^{c_1}}_{=\gamma_H^{c_1}} H_{t-1}\Delta \log H_t \underbrace{-(\phi_{c_1}^{c_1})^{-1} \phi_q^{c_1}}_{=\gamma_q^{c_1}} q_{t-1}\Delta \log q_t \\
& \underbrace{-(\phi_{c_1}^{c_1})^{-1} \phi_{c_2}^{c_1}}_{=\gamma_{c_2}^{c_1}} c_{2t-1}\Delta \log c_{2t} \\
& \underbrace{-(\phi_{c_1}^{c_1})^{-1} \phi_{h_1}^{c_1}}_{=\gamma_{h_1}^{c_1}} h_{1t-1}\Delta \log h_{1t} \underbrace{-(\phi_{c_1}^{c_1})^{-1} \phi_{h_2}^{c_1}}_{=\gamma_{h_2}^{c_1}} h_{2t-1}\Delta \log h_{2t} \Big\}.
\end{aligned}$$

B Full set of estimating equations

The set of estimating equations for housing expenditure, non-durables expenditure, commuting, and work hours in a reduced form setting is given by:

$$\begin{aligned}\log H_t = \alpha_0 + \alpha_y \log y_t + \alpha_a \log a_t + \alpha_q \log q_t + \alpha_{c_1} \log c_{1t} \\ + \alpha_{c_2} \log c_{2t} + \alpha_{h_1} \log h_{1t} + \alpha_{h_2} \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\alpha}_x + \varepsilon_t^H,\end{aligned} \tag{B.1}$$

$$\begin{aligned}\log q_t = \beta_0 + \beta_y \log y_t + \beta_a \log a_t + \beta_H \log H_t + \beta_{c_1} \log c_{1t} \\ + \beta_{c_2} \log c_{2t} + \beta_{h_1} \log h_{1t} + \beta_{h_2} \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\beta}_x + \varepsilon_t^q,\end{aligned} \tag{B.2}$$

$$\begin{aligned}\log c_{it} = \gamma_0^{c_i} + \eta_i \log w_{it} + \gamma_y^{c_i} \log y_t + \gamma_a^{c_i} \log a_t + \gamma_H^{c_i} \log H_t + \gamma_q^{c_i} \log q_t \\ + \gamma_{c_{-i}}^{c_i} \log c_{-it} + \gamma_{h_1}^{c_i} \log h_{1t} + \gamma_{h_2}^{c_i} \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\gamma^{c_i}}_x + \varepsilon_t^{c_i}, \quad i \in \{1, 2\},\end{aligned} \tag{B.3}$$

$$\begin{aligned}\log h_{it} = \delta_0^{h_i} + \delta_{w_i}^{h_i} \log w_{it} + \delta_y^{h_i} \log y_t + \delta_a^{h_i} \log a_t + \delta_H^{h_i} \log H_t + \delta_q^{h_i} \log q_t \\ + \delta_{c_1}^{h_i} \log c_{1t} + \delta_{c_2}^{h_i} \log c_{2t} + \delta_{h_{-i}}^{h_i} \log h_{-it} + \boldsymbol{x}_t^{'} \boldsymbol{\delta^{h_i}}_x + \varepsilon_t^{h_i}, \quad i \in \{1, 2\}.\end{aligned} \tag{B.4}$$

On the other hand, the full set of estimating equations in the life cycle setting is:

$$\begin{aligned}\Delta \log H_t = H_{t-1}^{-1} \times \Big\{ & \alpha_0 + \alpha_y \log y_{t-1} + \alpha_{\Delta y} \Delta \log y_t + \alpha_{\Delta a} \log a_{t-1} + \alpha_{\Delta a} \Delta \log a_t \\ & + \alpha_q q_{t-1} \Delta \log q_t + \alpha_{c_1} c_{1t-1} \Delta \log c_{1t} + \alpha_{c_2} c_{2t-1} \Delta \log c_{2t} \\ & + \alpha_{h_1} h_{1t-1} \Delta \log h_{1t} + \alpha_{h_2} h_{2t-1} \Delta \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\alpha}_x \Big\} + \varepsilon_t^H,\end{aligned} \tag{B.5}$$

$$\begin{aligned}\Delta \log q_t = q_{t-1}^{-1} \times \Big\{ & \beta_0 + \beta_y \log y_{t-1} + \beta_{\Delta y} \Delta \log y_t + \beta_{\Delta a} \log a_{t-1} + \beta_{\Delta a} \Delta \log a_t \\ & + \beta_H H_{t-1} \Delta \log q_t + \beta_{c_1} c_{1t-1} \Delta \log c_{1t} + \beta_{c_2} c_{2t-1} \Delta \log c_{2t} \\ & + \beta_{h_1} h_{1t-1} \Delta \log h_{1t} + \beta_{h_2} h_{2t-1} \Delta \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\beta}_x \Big\} + \varepsilon_t^q,\end{aligned} \tag{B.6}$$

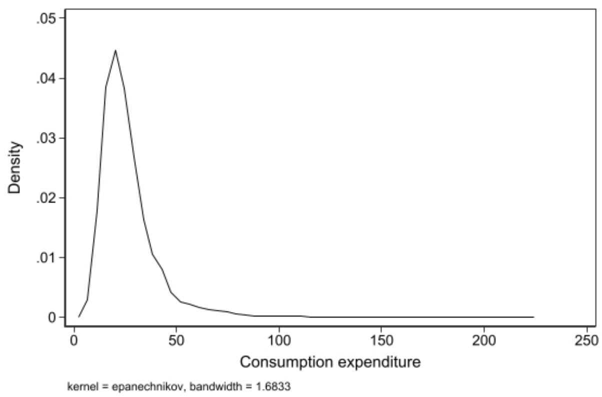
$$\begin{aligned}\Delta \log c_{it} = c_{it-1}^{-1} \times \Big\{ & \gamma_0^{c_i} + \gamma_y^{c_i} \log y_{t-1} + \gamma_{\Delta y}^{c_i} \Delta \log y_t + \gamma_{\Delta a}^{c_i} \log a_{t-1} + \gamma_{\Delta a}^{c_i} \Delta \log a_t \\ & + \eta_i \Delta \log w_{it} \\ & + \gamma_H^{c_i} H_{t-1} \Delta \log H_t + \gamma_q^{c_i} q_{t-1} \Delta \log q_t + \gamma_{c_{-i}}^{c_i} c_{-it-1} \Delta \log c_{-it} \\ & + \gamma_{h_1}^{c_i} h_{1t-1} \Delta \log h_{1t} + \gamma_{h_2}^{c_i} h_{2t-1} \Delta \log h_{2t} + \boldsymbol{x}_{it}^{'} \boldsymbol{\gamma}_x^{c_i} \Big\} + \varepsilon_t^{c_i}, \\ & i \in \{1, 2\}, \ -i \neq i,\end{aligned} \tag{B.7}$$

$$
\begin{aligned}
\Delta \log h_{it} = h_{it-1}^{-1} \times \Big\{ & \delta_0^{h_i} + \delta_y^{h_i} \log y_{t-1} + \delta_{\Delta y}^{h_i} \Delta \log y_t + \delta_{\Delta a}^{h_i} \log a_{t-1} + \delta_{\Delta a}^{h_i} \Delta \log a_t \\
& + \delta_{w_i}^{h_i} \Delta \log w_{it} \\
& + \delta_H^{h_i} H_{t-1} \Delta \log H_t + \delta_q^{h_i} q_{t-1} \Delta \log q_t + \delta_{c_1}^{h_i} c_{1t-1} \Delta \log c_{1t} \\
& + \delta_{c_2}^{h_i} c_{2t-1} \Delta \log c_{2t} + \delta_{h_{-i}}^{h_i} h_{-it-1} \Delta \log h_{-it} + \boldsymbol{x}_{it}^{'} \boldsymbol{\delta}_x^{h_i} \Big\} + \varepsilon_t^{c_i}, \\
& i \in \{1,2\},\ -i \neq i.
\end{aligned} \tag{B.8}
$$

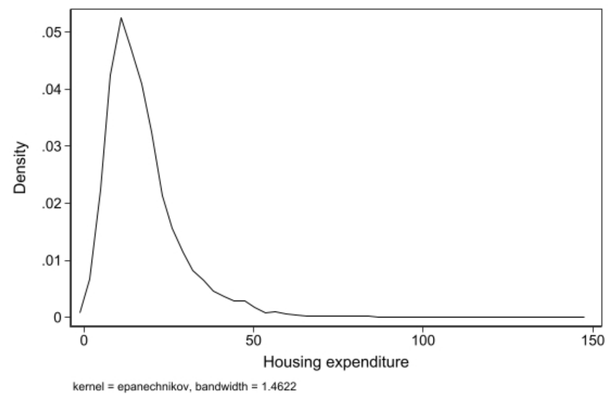
C Additional descriptives

Figure C.1: Density of key variables

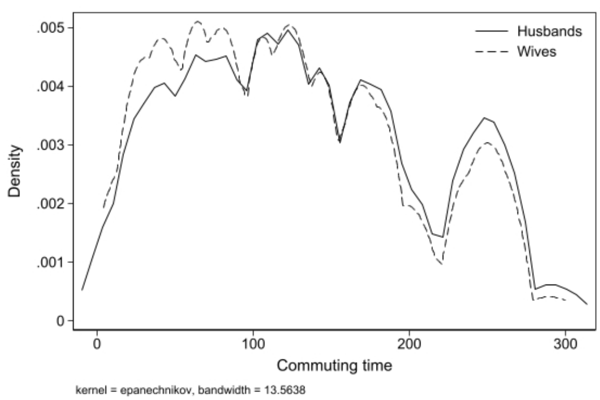
(a) Consumption expenditure (in $1,000)



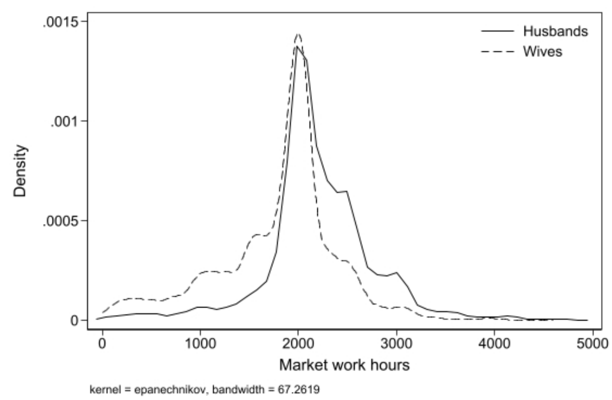
(b) Housing expenditure (in $1,000)



(c) Commuting time (hours/year)



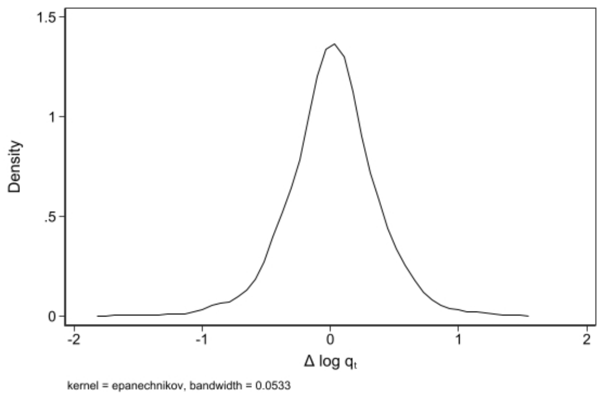
(d) Market work hours (hours/year)



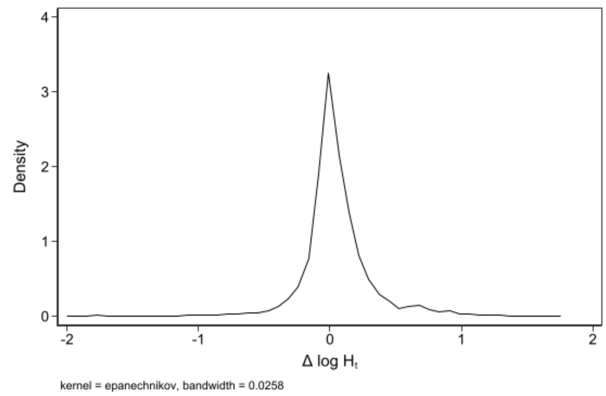
Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes.

Figure C.2: Density of growth rate of key variables

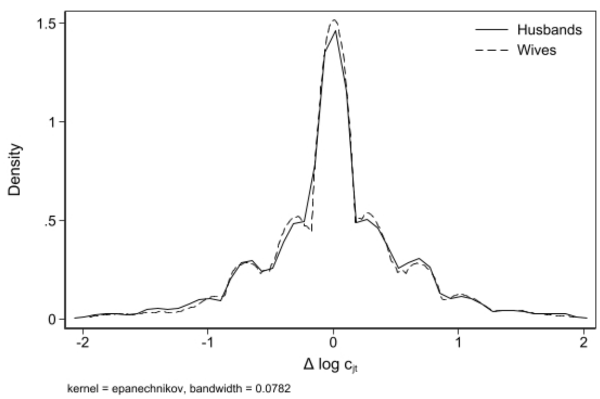
(a) Consumption expenditure (in $1,000)



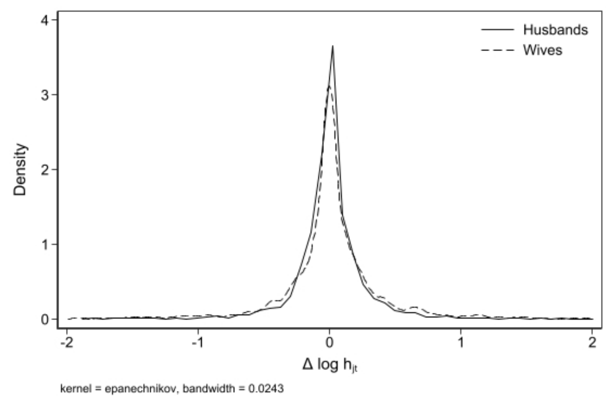
(b) Housing expenditure (in $1,000)



(c) Commuting time (hours/year)



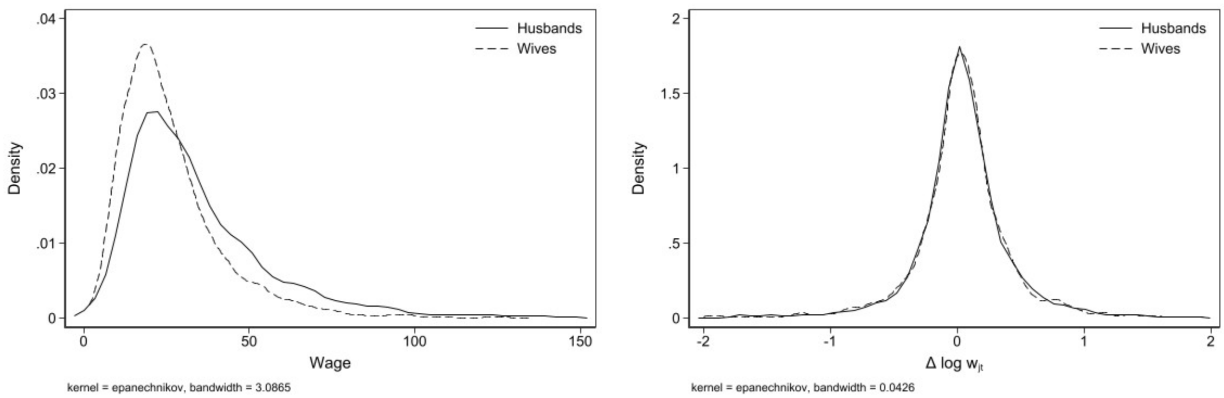
(d) Market work hours (hours/year)



Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes.

Figure C.3: Density of wages

(a) Wage (b) Wage growth rate



Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes.

Table C.1: Additional summary statistics

Individual variables	Males		Females		Difference	
	Mean	St.Dev.	Mean	St.Dev.	Diff.	p value
Age	43.81	10.92	42.29	10.87	1.520	0.000
White	0.920	0.272	0.924	0.266	-0.004	0.512
High school	0.263	0.441	0.204	0.403	0.059	0.000
Graduate	0.489	0.500	0.510	0.500	-0.021	0.061
Doctorate	0.186	0.389	0.259	0.438	-0.074	0.000
Household variables			Mean	St.Dev.		
Family size			3.213	1.165		
Number of children			1.012	1.129		
Households$\times$waves			4,021			
Households			1,183			

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes.

D Additional results

Table D.1: Additional reduced form results – other equations

Dependent variable:	$\log H_t$	$\log q_t$	$\log h_{1t}$	$\log h_{2t}$
$\log w_{it}$			-0.412***	-0.054
			(0.051)	(0.051)
$\log y_t$	0.444***	0.220***	0.692***	0.434***
	(0.033)	(0.024)	(0.061)	(0.058)
$\log a_t$	0.109***	0.018***	-0.017**	-0.050***
	(0.011)	(0.007)	(0.008)	(0.010)
$\log H_t$		0.092***	-0.063***	-0.129***
		(0.018)	(0.018)	(0.025)
$\log q_t$	0.160***		-0.025	0.061*
	(0.030)		(0.021)	(0.034)
$\log c_{1t}$	0.002	0.038***	-0.002	-0.055***
	(0.013)	(0.009)	(0.008)	(0.012)
$\log c_{2t}$	0.021*	0.014	-0.027***	0.032**
	(0.012)	(0.009)	(0.009)	(0.013)
$\log h_{1t}$	-0.114***	-0.011		-0.124***
	(0.031)	(0.022)		(0.032)
$\log h_{2t}$	-0.084***	0.029**	-0.163***	
	(0.018)	(0.013)	(0.021)	
Constant	0.760**	0.505**	7.446***	7.448***
	(0.341)	(0.234)	(0.160)	(0.248)
Demographics	Yes	Yes	Yes	Yes
Occupation f.e.	Yes	Yes	Yes	Yes
Region f.e.	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes
Observations	4,021	4,021	4,021	4,021

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes. Robust standard errors in parentheses, clustered at the household level.
*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

Table D.2: Additional reduced form results – demographics

Dependent variable:	$\log H_t$	$\log q_t$	$\log c_{1t}$	$\log c_{2t}$	$\log h_{1t}$	$\log h_{2t}$
Male age	-0.000	0.006**	0.001		-0.004***	
	(0.004)	(0.002)	(0.002)		(0.001)	
Female age	-0.004	-0.001		-0.008***		-0.003**
	(0.004)	(0.002)		(0.002)		(0.001)
Male high school	0.045	-0.073**	0.020		0.073*	
	(0.068)	(0.031)	(0.095)		(0.038)	
Male graduate	0.120*	-0.092***	0.020		0.023	
	(0.066)	(0.031)	(0.095)		(0.039)	
Male doctorate	0.130*	-0.061	-0.035		-0.020	
	(0.072)	(0.038)	(0.108)		(0.048)	
Female high school	0.123	-0.027		-0.098		-0.065
	(0.089)	(0.053)		(0.099)		(0.074)
Female graduate	0.132	0.057		-0.173*		-0.147**
	(0.088)	(0.053)		(0.091)		(0.073)
Female doctorate	0.193**	0.080		-0.267***		-0.140*
	(0.090)	(0.057)		(0.101)		(0.079)
Male white	0.033	0.027	-0.007		0.054	
	(0.064)	(0.043)	(0.068)		(0.035)	
Female white	-0.027	0.088**		-0.097		-0.129***
	(0.066)	(0.043)		(0.078)		(0.039)
Family size	0.025	0.209***	0.005	-0.052	0.042***	0.019
	(0.021)	(0.018)	(0.044)	(0.039)	(0.013)	(0.021)
# children	-0.008	-0.109***	0.002	-0.016	-0.042***	-0.092***
	(0.021)	(0.019)	(0.044)	(0.041)	(0.016)	(0.023)
Observations	4,021	4,021	4,021	4,021	4,021	4,021

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes. Robust standard errors in parentheses, clustered at the household level.
*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

Table D.3: Additional first difference estimates – other equations

Dependent variable:	$\Delta \log H_t$	$\Delta \log q_t$	$\Delta \log h_{1t}$	$\Delta \log h_{2t}$
$\Delta \log w_{it}$			-84.25***	-31.32*
			(23.99)	(16.50)
$\log y_{t-1}$	0.039	2.191***	18.25	13.18
	(0.164)	(0.297)	(25.54)	(20.55)
$\Delta \log y_t$	0.035	1.172**	618.4***	38.52
	(0.187)	(0.518)	(76.36)	(30.56)
$\log a_{t-1}$	0.364***	0.104	-29.63***	16.13
	(0.085)	(0.106)	(11.18)	(16.26)
$\Delta \log a_t$	0.377***	-0.032	33.29***	-24.11
	(0.113)	(0.145)	(12.58)	(15.75)
$\Delta \log H_t$		0.123***	2.838	-4.860
		(0.036)	(3.507)	(2.986)
$\Delta \log q_t$	0.008		-3.386***	0.353
	(0.009)		(1.164)	(1.112)
$\Delta \log c_{1t}$	-0.000	0.000	0.037	-0.248***
	(0.000)	(0.001)	(0.066)	(0.061)
$\Delta \log c_{2t}$	0.001	0.000	-0.104	0.117
	(0.001)	(0.001)	(0.070)	(0.109)
$\Delta \log h_{1t}$	-0.000	-0.000		0.004
	(0.001)	(0.000)		(0.018)
$\Delta \log h_{2t}$	-0.000	0.000	-0.025	
	(0.000)	(0.000)	(0.019)	
Constant	-0.050***	-0.402**	-0.057***	-0.089***
	(0.012)	(0.021)	(0.014)	(0.014)
Demographics	Yes	Yes	Yes	Yes
Household f.e.	Yes	Yes	Yes	Yes
Region f.e.	Yes	Yes	Yes	Yes
Observations	2,820	2,820	2,820	2,820

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes. Robust standard errors in parentheses, clustered at the household level.
*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

Table D.4: Additional first difference estimates – demographics

Dependent variable:	$\Delta \log H_t$	$\Delta \log q_t$	$\Delta \log c_{1t}$	$\Delta \log c_{2t}$	$\Delta \log h_{1t}$	$\Delta \log h_{2t}$
Male age	-0.094***	0.044	-0.243**		0.301	
	(0.022)	(0.033)	(0.109)		(1.480)	
Female age	0.050**	-0.063*		-0.251**		0.004
	(0.021)	(0.034)		(0.124)		(1.575)
Male high school	0.337	-1.209*	3.302		304.675***	
	(0.333)	(0.682)	(4.211)		(60.066)	
Male graduate	0.311	-1.537**	-1.613		258.757***	
	(0.331)	(0.661)	(4.059)		(66.327)	
Male doctorate	0.384	-0.850	-3.364		296.578***	
	(0.393)	(0.716)	(4.481)		(72.131)	
Female high school	0.422*	-0.161		-5.073		75.307
	(0.250)	(1.026)		(6.605)		(75.563)
Female graduate	0.116	0.702		-3.567		115.365*
	(0.275)	(1.011)		(6.508)		(65.803)
Female doctorate	0.743**	1.176		-3.871		155.382**
	(0.321)	(1.071)		(6.982)		(74.481)
Male white	0.239	0.564	-8.812*		270.470***	
	(0.256)	(0.505)	(4.864)		(62.421)	
Female white	0.207	0.297		1.160		-45.028
	(0.311)	(0.549)		(2.288)		(49.933)
Family size	0.124	1.053***	2.181	2.801**	-74.954**	31.201
	(0.133)	(0.329)	(2.448)	(1.376)	(36.492)	(23.324)
# children	-0.214	0.020	-4.867*	-4.383***	38.188	-47.598*
	(0.144)	(0.328)	(2.787)	(1.609)	(41.434)	(28.799)
Δ family size	-0.013	0.016	-0.413	-2.936*	-27.793	-12.003
	(0.156)	(0.449)	(1.646)	(1.537)	(31.208)	(28.199)
Δ # children	0.215	-1.686***	0.475	5.322***	-53.077	-19.469
	(0.198)	(0.536)	(2.202)	(1.868)	(45.472)	(33.180)
Observations	2,820	2,820	2,820	2,820	2,820	2,820

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes. Robust standard errors in parentheses, clustered at the household level.
*** significant at the 1%; ** significant at the 5%; * significant at the 10%.