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ABSTRACT

Commutung, Wages, and Household Behavior*

Commuting is a significant aspect of workers' daily routines and is associated with various negative outcomes. Traditional literature often models commuting from an urban perspective, focusing on the trade-off between commuting and housing. This paper offers an alternative view by using a household model as the theoretical basis to explore the interconnectedness of couples' commuting, wages, labor supply, and consumption. Using data from the PSID for the years 2011-2019, results indicate a positive and highly significant correlation between wages and commuting when analyzed cross-sectionally. However, changes in wages and commuting over an individual's life cycle are not related. Additionally, commuting appears to be associated with spousal commuting, household earnings, and wealth, while higher expenditures are linked to longer commutes, but again, only cross-sectionally.

JEL Classification: D12, D15, J22, J31
Keywords: commuting, household behavior, wages, PSID

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1 Introduction

Commuting, a significant aspect of workers' daily mobility, has been witnessing a steady increase in duration in numerous developed nations. This trend, highlighted in recent studies (Kirby and LeSage, 2009; Giménez-Nadal et al., 2022), underscores the relevance of analyzing commuting behaviors. The implications of commuting are profound, affecting not only the wellbeing of workers and firms but also broader societal aspects. These include adverse impacts on health (Künn-Nelen, 2016), subjective wellbeing and happiness (Kahneman et al., 2004; Kahneman and Krueger, 2006; Roberts et al., 2011; Dickerson et al., 2014), increased stress levels (Stutzer and Frey, 2008; Gottholmseder et al., 2009), absenteeism due to sickness (Van Ommeren and Gutiérrez-i Puigarnau, 2011), reduced productivity (Grinza and Rycx, 2020), and even tendencies towards shirking (Ross and Zenou, 2008; Giménez-Nadal et al., 2018). Additionally, the choice of commuting modes has significant environmental repercussions (Long and Szeto, 2019; Vosough et al., 2022).

This paper investigates the commuting behaviors of workers in dual-earner households, examining the interconnections between commuting time, wages, household labor supply, and consumption within a comprehensive household model, drawing upon concepts from urban and job-search models (Ross and Zenou, 2008; Van Ommeren and van der Straaten, 2008), while also integrating recent advances in household economics (Blundell et al., 2016). We derive the model's optimality conditions in both static and life cycle frameworks and subsequently estimate household behavior using data from the Panel Study of Income Dynamics (PSID) spanning 2011-2019. By focusing on intra-household factors, this study provides a nuanced understanding of how commuting, wages, labor supply, and consumption interact within households.

Our research aims to fill the gap left by previous studies, which often focused on individual worker samples, thereby neglecting the complex dynamics present within households. By developing a theoretical model that incorporates both static and life cycle perspectives, we can better understand the factors influencing commuting behaviors in dual-earner households. This paper addresses how these elements interact and the implications of these interactions for broader economic and societal outcomes.

Existing literature has recognized the significance of intra-household factors in commuting models. However, empirical studies have often focused on individual worker samples, neglecting the complexities of household behaviors due to the scarcity of detailed household data. Exceptions include the works of Roberts et al. (2011) and De Palma et al. (2015), who analyze commuting and wellbeing 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). Finally, the literature has recently addressed how commuting relates to other daily activities, including labor supply, leisure activities, childcare, and shopping (Gutiérrez-i Puigarnau and van Ommeren, 2015; Oakil et al., 2016; Giménez-Nadal et al., 2018; Chidambaram and Scheiner, 2019).[1]

An important branch of the existing literature on commuting has analyzed its relation to wages, dating back to Leigh (1986), who concluded that white workers were paid compensating wages for long commutes in the US. Van Ommeren et al. (2000) and Albouy and Lue (2015) also found that employers were willing to pay higher wages compensating for longer commutes in the Netherlands and the US, respectively, and Renkow and Hoover (2000) estimated a positive elasticity between wages and commutes in the US. Gutiérrez-i Puigarnau and van Ommeren (2010) found a positive correlation between wages and commuting in Germany, in line with the causal results of Mulalic et al. (2014) for Denmark.

Our contribution is twofold. Firstly, we develop a model that blends key elements from job-search and household models, allowing us to scrutinize the interplay of various factors such as commuting times, wages, spouses' labor supplies, housing, and consumption within households. This examination is undertaken initially in a straightforward, reduced-form context, and subsequently within a more complex life cycle framework. By integrating concepts from urban and job-search models with recent advances in household economics, we provide a comprehensive analysis of how these elements interact over both short and long-term horizons.

Secondly, we present an empirical exploration of these interrelations using data from the PSID, offering insights that could inform policymakers and urban planners in understanding the implications of specific measures on household behaviors and wellbeing in a broad context. Our findings reveal important cross-sectional relationships between commuting and wages, as well as dynamic interactions over the life cycle, highlighting the need for policies that consider the diverse impacts of commuting on household welfare.

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), the quasi-reduced-form life cycle approach (4.2), and the heterogeneity analysis (4.3). Section 5 discusses these results, and finally Section 6 concludes.

[1]See Giménez-Nadal et al. (2023) for a recent review.

2 Model

In this section, we introduce a model that characterizes household behavior, focused on households composed of two working spouses. Assume that a household j is formed by working spouses $i = 1, 2$, and lives for periods $t = 0, \ldots, T$.[2] 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}.[3] 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.

The model constrains the household to a budget, wherein wages and commuting are interrelated (e.g., urban efficiency wages, wage premia, specialization, etc.).[4] 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:

$$y_t = w_{1t}\left(h_{1t} + \eta_{1t}c_{1t}\right) + w_{2t}\left(h_{2t} + \eta_{2t}c_{2t}\right),$$

where η_{it} represents the relationship between spouse i earnings and commuting time. 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 $\Theta_t = \{H_t, q_t, c_{1t}, c_{2t}, h_{1t}, h_{2t}, a_{t+1}\}$.

Both household utility and the budget constraint capture elements of urban models of

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

[3]Van Ommeren and Fosgerau (2009) found and conclude that commuting does produce disutility to workers, and quantify such disutility in around twice the worker net wage.

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

commuting time, as housing, commuting being potentially related to earnings, or the trade-off between housing and commuting in a monocentric city (Alonso, 1964; Mills, 1967). The 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 or urban sprawl, among others. See recent investigations by Huai et al. (2021) and Liotta et al. (2022).

The potential trade-off between commuting and housing is reflected in this household model in a different way. The household utility function explicitly assumes that workers dislike commuting and enjoy housing, as in urban models. Thus, households should look on one hand for residing in the business district (i.e., extremely high housing costs and very short commutes). However, the budget constraint is also dependent of 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 not only between housing and commuting, but between all the key endogenous variables of the model.

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 $t \geq 1$:[5]

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

2.1 Development in a static, reduced form setting

Taking logs, we can express the first order conditions (3) as:

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

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:

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

It is important to note that we do allow for interdependence between the endogenous variables in the model. An alternative approach would assume separability, i.e. that the decisions about how much labor to supply, how much time to commute, how much to consume, and how much to spend in housing are made independently. We decided to allow for these interdependencies in the model, which allows us to conclude if these behaviors are related or not in the empirical exercise. We return to this below.

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

2.2 Development in a dynamic setting

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

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

Next, we apply a standard log-linealization 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.[6] We then can write the log-linealization of marginal utilities, in quasi-reduced form, as:

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

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

2.3 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

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

in Theloudis et al. (2023):

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

Similarly, compensation rates are unobserved. We assume they depend on labor force characteristics $\boldsymbol{x}_{it}^{LF}$:[7]

$$\log(\eta_{it} w_{it}) \approx \eta_i(\boldsymbol{x}_{it}^{LF}) \log w_{it},$$
$$\Delta \log(\eta_{it} w_{it}) \approx \eta_i(\Delta \boldsymbol{x}_{it}^{LF}) \Delta \log w_{it},$$

where $\eta_i(\boldsymbol{x}_{it}^{LF})$ and $\eta_i(\Delta \boldsymbol{x}_{it}^{LF})$ are unobserved functions that relate wages and commuting.

An important remark is that wages are tipically exogenous (e.g., right-hand-side) variables in household models (e.g. Chiappori et al., 2002; Mazzocco, 2007; Lise and Yamada, 2019). This contrasts with some urban models in which wages are endogenous (left-hand-side) variables, such as Ross and Zenou (2008), Ruppert et al. (2009) and Fu and Ross (2013), where commuting is a regressor. 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 equations (4) can be expreesed, for $-i \neq i$, as:

$$\begin{aligned} \log H_t = {} & \alpha_0 + \alpha_y \log y_t + \alpha_a \log a_t + \alpha_q \log q_t + \alpha_{c_1} \log c_{1t} \\ & + \alpha_{c_2} \log c_{2t} + \alpha_{h_1} \log h_{1t} + \alpha_{h_2} \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\alpha}_x + \varepsilon_t^H, \end{aligned} \tag{7}$$

$$\begin{aligned} \log q_t = {} & \beta_0 + \beta_y \log y_t + \beta_a \log a_t + \beta_H \log H_t + \beta_{c_1} \log c_{1t} \\ & + \beta_{c_2} \log c_{2t} + \beta_{h_1} \log h_{1t} + \beta_{h_2} \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\beta}_x + \varepsilon_t^q, \end{aligned} \tag{8}$$

$$\begin{aligned} \log c_{it} = {} & \gamma_0^{c_i} + \eta_i \log w_{it} + \gamma_y^{c_i} \log y_t + \gamma_a^{c_i} \log a_t + \gamma_H^{c_i} \log H_t + \gamma_q^{c_i} \log q_t \\ & + \gamma_{c_{-i}}^{c_i} \log c_{-it} + \gamma_{h_1}^{c_i} \log h_{1t} + \gamma_{h_2}^{c_i} \log h_{2t} + \boldsymbol{x}_t^{'} \boldsymbol{\gamma^{c_i}}_x + \varepsilon_t^{c_i}, \quad i \in \{1, 2\}, \end{aligned} \tag{9}$$

$$\begin{aligned} \log h_{it} = {} & \delta_0^{h_i} + \delta_{w_i}^{h_i} \log w_{it} + \delta_y^{h_i} \log y_t + \delta_a^{h_i} \log a_t + \delta_H^{h_i} \log H_t + \delta_q^{h_i} \log q_t \\ & + \delta_{c_1}^{h_i} \log c_{1t} + \delta_{c_2}^{h_i} \log c_{2t} + \delta_{h_{-i}}^{h_i} \log h_{-it} + \boldsymbol{x}_t^{'} \boldsymbol{\delta^{h_i}}_x + \varepsilon_t^{h_i}, \quad i \in \{1, 2\}. \end{aligned} \tag{10}$$

This formulation allows for the analysis of various interdependencies within the household

[7] $\boldsymbol{x}_{it}^{LF}$ may include education, occupation, etc.

model, reflecting the relationships between wages, labor supply, commuting, and household expenditure decisions. 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, equations (7)-(10) cannot capture how variables 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 housing expenditure, consumption, spouses' commuting times, and spouses' market work hours are then, assembling (6) and the modeling choices:

$$
\begin{aligned}
\Delta \log H_t = H_{t-1}^{-1} \times \Big\{ & \alpha_0 + \alpha_y \log y_{t-1} + \alpha_{\Delta y} \Delta \log y_t + \alpha_{\Delta a} \log a_{t-1} + \alpha_{\Delta a} \Delta \log a_t \\
& + \alpha_q q_{t-1} \Delta \log q_t + \alpha_{c_1} c_{1t-1} \Delta \log c_{1t} + \alpha_{c_2} c_{2t-1} \Delta \log c_{2t} \\
& + \alpha_{h_1} h_{1t-1} \Delta \log h_{1t} + \alpha_{h_2} h_{2t-1} \Delta \log h_{2t} + \boldsymbol{x}_t' \boldsymbol{\alpha}_x \Big\} + \varepsilon_t^H,
\end{aligned} \tag{11}
$$

$$
\begin{aligned}
\Delta \log q_t = q_{t-1}^{-1} \times \Big\{ & \beta_0 + \beta_y \log y_{t-1} + \beta_{\Delta y} \Delta \log y_t + \beta_{\Delta a} \log a_{t-1} + \beta_{\Delta a} \Delta \log a_t \\
& + \beta_H H_{t-1} \Delta \log q_t + \beta_{c_1} c_{1t-1} \Delta \log c_{1t} + \beta_{c_2} c_{2t-1} \Delta \log c_{2t} \\
& + \beta_{h_1} h_{1t-1} \Delta \log h_{1t} + \beta_{h_2} h_{2t-1} \Delta \log h_{2t} + \boldsymbol{x}_t' \boldsymbol{\beta}_x \Big\} + \varepsilon_t^q,
\end{aligned} \tag{12}
$$

$$
\begin{aligned}
\Delta \log c_{it} = c_{it-1}^{-1} \times \Big\{ & \gamma_0^{c_i} + \gamma_y^{c_i} \log y_{t-1} + \gamma_{\Delta y}^{c_i} \Delta \log y_t + \gamma_{\Delta a}^{c_i} \log a_{t-1} + \gamma_{\Delta a}^{c_i} \Delta \log a_t \\
& + \eta_i \Delta \log w_{it} \\
& + \gamma_H^{c_i} H_{t-1} \Delta \log H_t + \gamma_q^{c_i} q_{t-1} \Delta \log q_t + \gamma_{c_{-i}}^{c_i} c_{-it-1} \Delta \log c_{-it} \\
& + \gamma_{h_1}^{c_i} h_{1t-1} \Delta \log h_{1t} + \gamma_{h_2}^{c_i} h_{2t-1} \Delta \log h_{2t} + \boldsymbol{x}_{it}' \boldsymbol{\gamma}_x^{c_i} \Big\} + \varepsilon_t^{c_i}, \\
& i \in \{1, 2\}, \ -i \neq i,
\end{aligned} \tag{13}
$$

$$
\begin{aligned}
\Delta \log h_{it} = h_{it-1}^{-1} \times \Big\{ & \delta_0^{h_i} + \delta_y^{h_i} \log y_{t-1} + \delta_{\Delta y}^{h_i} \Delta \log y_t + \delta_{\Delta a}^{h_i} \log a_{t-1} + \delta_{\Delta a}^{h_i} \Delta \log a_t \\
& + \delta_{w_i}^{h_i} \Delta \log w_{it} \\
& + \delta_H^{h_i} H_{t-1} \Delta \log H_t + \delta_q^{h_i} q_{t-1} \Delta \log q_t + \delta_{c_1}^{h_i} c_{1t-1} \Delta \log c_{1t} \\
& + \delta_{c_2}^{h_i} c_{2t-1} \Delta \log c_{2t} + \delta_{h_{-i}}^{h_i} h_{-it-1} \Delta \log h_{-it} + \boldsymbol{x}_{it}' \boldsymbol{\delta}_x^{h_i} \Big\} + \varepsilon_t^{c_i}, \\
& i \in \{1, 2\}, \ -i \neq i.
\end{aligned} \tag{14}
$$

Deriving equations in a life cycle settings provides additional insights to the static framework. 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).

We assume in estimating equations (9) and (13) that coefficients η_i, $i \in \{1, 2\}$ are first fixed. We then allow η's to change by occupation and by education level, $\eta_i = \eta_i(\text{educ}_{it}, \text{occ}_{it})$, $i \in \{1, 2\}$. This way, we study if the correlations between wages and commuting are homogeneous in terms of education and occupation, or conversely depend on worker labor force characteristics. We return to this heterogeneity analysis below.

2.4 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, 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 household housing and consumption, spouses' commuting times, and spouses' labor supplies. These equations are derived in both a 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 impacts of housing expenditure, consumption, and both male and female market work hours on household commuting times, 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 influenced by 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, this relationship 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. This complements existing analyses on commuting and wages in different contexts. For instance, Ross and Zenou (2008) 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. The equations also allow us to examine whether the potential relationship between wages and commuting is homogeneous or varies based on worker characteristics such as education, occupations, or other observables.

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. 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, while meeting the aforementioned criteria, 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., 2023).

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.[8] 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.[9]

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).[10] 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.

Table 1 presents the summary statistics for key variables.[11] 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).

[8]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.

[9]Monetary amounts (wages, earnings, consumption, wealth) are all expressed in 2018 dollars.

[10]We define expenditure following existing research using the PSID (Theloudis, 2021; Theloudis et al., 2023).

[11]Figures B.1 and B.2 in the Appendix B show the distribution of the key variables; Figure B.3 shows the distribution of wages.

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. Additional descriptives are shown in Table B.1 in the Appendix B

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 (e.g. Sandow, 2008; Roberts et al., 2011; Dargay and Clark, 2012; McQuaid and Chen, 2012; Le Barbanchon et al., 2021; Giménez-Nadal et al., 2022).

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 such as (7)-(10), or the dynamic equations (11)-(14), for $i \in \{1, 2\}$, several approaches are feasible. A straightforward estimation of each equation using OLS could recover 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 equations both in the static reduced-form setting, and in the dynamic quasi-reduced form scenario. 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), and because earnings influence residential location choices (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 the right-and-side variables, but 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. We tried instrumenting wages using various Mincer-style equations, but unfortunately we consistently failed at instrumenting wages, overidentifying wages in all our attempts. As a consequence, our empirical analysis is one of *correlations*, and not causal effects, which is an important limitation of the analysis.

4 Results

4.1 Reduced form results

Table 2 shows the results of estimating (9) for husbands and wives. Columns (1) and (2) show GMM estimates without household fixed effects, whereas Columns (3) and (4) show estimates including household fixed effects.[12] Estimates on the remaining household dependent variables, as well as results for the demographics, are shown in the Appendix C.

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 the relation with male commuting is not significant at standard levels. On the other hand, it is wealth which is found to be negatively related to husband commuting, but not to wife's commuting. In other words, husband commuting behavior seems more sensitive to wealth, whereas wife commuting is more sensitive to earnings.

Housing expenditure is not related to commuting. However, non-durables consumption expenditure relates positively to husband commuting time, but not to the wife's. We also find a strong connexion between spouses' commuting, as coefficients associated to $-i$'s commuting are positive statistically significant. This suggests that there is some form of complementarity between spouses' commuting time, although we remain agnostic regarding the potential channels that drive such complementarity. Finally, commuting and own labor supply are related positively only for wives, while spouses' hours of work seem not to be related to commuting times.

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

Table 2: Reduced form results

	Baseline		Household fixed effects	
Dep. var.: $\log c_{it}$ Variables	Males $i = 1$	Females $i = 2$	Males $i = 1$	Females $i = 2$
$\log w_{it}$	0.252***	0.322***	0.044	0.115***
	(0.054)	(0.043)	(0.044)	(0.032)
$\log y_t$	-0.022	-0.168***	-0.010	-0.093**
	(0.075)	(0.056)	(0.066)	(0.047)
$\log a_t$	-0.077***	-0.010	-0.027**	0.011
	(0.015)	(0.016)	(0.012)	(0.013)
$\log H_t$	0.008	0.041	0.088**	0.163***
	(0.040)	(0.038)	(0.039)	(0.039)
$\log q_t$	0.219***	0.065	0.065***	0.118***
	(0.048)	(0.050)	(0.034)	(0.034)
$\log c_{-it}$	0.316***	0.331***	0.360***	0.365***
	(0.027)	(0.027)	(0.015)	(0.015)
$\log h_{1t}$	-0.014	0.009	0.009	-0.038
	(0.051)	(0.047)	(0.043)	(0.035)
$\log h_{2t}$	-0.046	0.073**	-0.020	0.053**
	(0.031)	(0.030)	(0.024)	(0.024)
Constant	2.882***	2.782***	1.937***	2.432***
	(0.473)	(0.482)	(0.499)	(0.474)
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
Household f.e.	No	No	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. Housing, consumption, and hours equations are shown in Table C.1, and additional estimates are shown in Table C.2 in the Appendix C.
*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

Columns (3) and (4) show estimates controlling for household fixed effects, to exploit the panel structure of the data and net out household unobservables. Intriguingly, once we net out household unobservables by including household fixed effects, the conditional correlation between husband commuting time and wages becomes not statistically significant. However, among wives, said correlation remains positive and statistically significant at standard levels.

This is to say, results suggest the existence of a cross-sectional correlation between wages and commuting time (those who commute longer times have higher wages), but it is explained by household characteristics, especially among husbands. Once those characteristics are net out, the correlation disappears among husbands, but remains among wives, although the magnitude decreases significantly ($p < 0.001$).

4.2 Life cycle results

Estimates of the life cycle equation (13) are shown in Table 3, for husbands and wives. Estimates on the remaining household dependent variables, as well as results for the demographics, are shown in the Appendix C. Overall, the results indicate that the growth rate of commuting time of spouses is relatively steady. First of all, estimates suggest that changes in wages do not relate to changes in commuting times, nor for husbands neither for 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. It suggests again 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.

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

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, but the 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. Regarding spousal commuting time, and spouses supplies of labor, the associated coefficients are all not statistically significant at standard levels. As a consequence, we do not find evidence supporting dynamic correlations between spouses' commuting times, neither between spouses labor supplies and commuting times.

Table 3: Estimates of first difference equations

Dep. var.: $\Delta \log c_{it}$ Variables	Males $i = 1$	Females $i = 2$
$\Delta \log w_{it}$	-3.595	1.244
	(2.777)	(2.302)
$\log y_{t-1}$	8.566***	6.290***
	(1.478)	(1.422)
$\Delta \log y_t$	7.810*	-1.153
	(4.733)	(2.728)
$\log a_{t-1}$	-1.219*	-1.643**
	(0.721)	(0.664)
$\Delta \log a_t$	0.381	-0.870
	(0.984)	(0.947)
$\Delta \log H_t$	-0.220*	0.311
	(0.121)	(0.223)
$\Delta \log q_t$	0.207***	0.097
	(0.072)	(0.059)
$\Delta \log c_{-it}$	0.004	0.003
	(0.010)	(0.003)
$\Delta \log h_{1t}$	-0.002	0.001
	(0.001)	(0.001)
$\Delta \log h_{2t}$	-0.001	0.001
	(0.001)	(0.001)
Constant	-0.210***	-0.212***
	(0.016)	(0.018)
Demographics	Yes	Yes
Occupation f.e.	Yes	Yes
Region f.e.	Yes	Yes
Year f.e.	Yes	Yes
Observations	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. Housing, consumption, and hours equations are shown in Table C.3, and additional estimates are shown in Table C.4 in the Appendix C.
*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

4.3 Heterogeneity

We now estimate both the static and the life cycle equations, but allow parameters η_{it} to be heterogeneous in terms of education, and in terms of worker occupation.[13] The PSID used the 2000 Census to code workers' first occupation between 2003 and 2015, and the 4-digit 2010 Census occupation classification since 2017. We use these classifications to aggregate occupations into five categories: 1) management, professional and related occupations; 2) service occupations; 3) sales and office occupations, 4) natural resources, construction and maintenance occupations; and 5) production, transportation, material moving and other occupations.

Table 4: Main results with heterogeneity

Dependent variable:	$\log c_{it}$		$\Delta \log c_{it}$	
Partial effect of wages ($\log w_{it}$, $\Delta \log w_{it}$) for:	Males $i=1$	Females $i=2$	Males $i=1$	Females $i=2$
Non-high school graduates	0.166*	0.250	5.873	10.139
	(0.097)	(0.154)	(8.171)	(16.806)
High school graduates	0.199***	0.152**	-4.159	0.730
	(0.050)	(0.061)	(0.197)	(3.750)
Bachelor degree graduates	0.311***	0.418***	-5.194	1.385
	(0.047)	(0.036)	(4.382)	(2.449)
Doctorates	0.232***	0.245***	-3.267	0.288
	(0.056)	(0.047)	(3.703)	(4.481)
Production, transportation, other	0.174***	0.344***	-5.626	-7.444
	(0.034)	(0.115)	(7.820)	(4.537)
Management, professional, related	0.300***	0.340***	-0.036	2.796
	(0.047)	(0.036)	(3.220)	(2.412)
Service occupations	0.254***	0.240***	3.457	3.846
	(0.066)	(0.066)	(6.235)	(4.532)
Sales, office occupations	0.255***	0.331***	-10.154***	-5.697*
	(0.065)	(0.048)	(2.840)	(3.216)
Natural res., construction, maintenance	0.193***	0.428	-3.297	-0.822
	(0.061)	(0.408)	(3.917)	(5.160)

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, computed using the delta method. Static reduced form estimates do not include household fixed effects.
*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

[13] An alternative approach would be to estimate equations household-by-household. Unfortunately, the PSID does not include long time series per household, thus making impossible this approach.

The results for the specific η_{it} for each education level, and each occupation are shown in Table 4. Columns 1 and 2 show the conditional correlations between $\log w_{it}$ and $\log c_{it}$ for husbands and wives, in the reduced form static setting. Columns 3 and 4 show results for the life cycle approach, i.e., the correlations between $\Delta \log w_{it}$ and $\Delta \log c_{it}$ for each education and occupation group analyzed. All the results for housing, consumption, and hours equation remained similar to those without heterogeneity.

Regarding estimates of the static approach, results show that the correlation between wages and commuting time is positive and marginally significant for husbands with low levels of formal education, and not statistically significant for similar wives. However, the correlation becomes significant as both husbands and wives increase their education level, being sizeable and statistically significant for husbands who have completed high-school, for both husbands and wives who have a bachelor degree, and for husbands and wives who are doctorate. However, despite quantitative differences, our results also suggest that the correlations are not different across individuals with high school education, a bachelor degree, and a doctorate, at standard levels.

Regarding heterogeneity in terms of occupation, for husbands, our results suggest that there is a positive correlation between wages and commuting time for every occupation category analyzed. This correlation seems to be larger among those husbands in management, professional, and related occupations; in fact, estimates suggest that among workers in such occupation group the correlation is statistically larger than for workers in the remaining occupation groups ($p = 0.047$). However, estimates do not allow us to conclude that there are statistically significant differences across the remaining occupation groups. For wives, however, results suggest that the correlation between wages and commuting is similar for all the occupation groups, being positive and statistically significant for all the occupations but for natural resources, construction and maintenance occupations, for which the correlation is positive but not statistically significant.[14]

life cycle estimates, on the other hand, suggest that the correlation between changes in wages and changes in commuting times is not statistically significant for every education group considered, both for husbands and for wives. In other words, the lack of statistical significance in the baseline correlation estimated in Table 3 does not come from heterogeneity in terms of worker education. However, despite the lack of statistical significance, the correlation seems larger among workers with lower education level than among workers with high education.[15] As for heterogeneity in terms of occupation, the correlation between the

[14]Only the 1.4% of the wives in the sample work in natural resources, construction and maintenance occupations, which might explain the lack of statistical significance for such group.

[15]Statistical significance is challenging in the life cycle context given the limited sample size and the flexible

growth rate of wages and the commuting growth rate is negative and statistically significant among wives and husbands in sales and office occupations, and not significant at standard levels for female and male workers in the remaining occupations.

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 suggests 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 US white 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 for each commuting kilometer of about \$0.25, focusing on commuting distance rather than on commuting time, close to an elasticity of 0.4.[16] 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 occupations with supervision, in an urban efficiency wage setting.[17] 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. Mulalic et al. (2014) use a quasi-experimental scenario and find that a 1km increase in commuting distance induces a moderate wage increase of about 0.15% using Danish data. Le Barbanchon et al. (2021) use French administrative data to quantify the value of commute at 80% of wages for males, and 98% among females. Also using French

estimating equations.

[16] Previous analyses also found a marginal willingness to pay of 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.

[17] Giménez-Nadal et al. (2018) concluded similarly using US time use surveys.

data, Aboulkacem and Nedoncelle (2022) find that wage increases translate into increased commuting distance.[18]

We contribute to the growing literature on commuting and wages by analyzing the relationship between them within a household model, which accounts for the inter relations between commuting and other behaviors in the household. In doing so, we also analyze the relationship between labor supply and commuting (e.g. Gutiérrez-i Puigarnau and van Ommeren, 2010, 2015), although our estimates show that such correlation is only statistically significant among wives, but not among husbands. Furthermore, our estimates also suggest that households unobserved observables barely explain the correlation between commuting and work hours among wives. Future research should delve into this correlation, explaining gender differences.

We also study potential heterogeneity, and find that the correlation between wages and commuting is especially relevant among non-low educated workers. This suggests that specialization of these workers may play a role in wage premia for longer commutes. We also find that the correlation is not heterogeneous in terms of occupation. These estimates contrast with results from urban efficiency models, who argue that it is among supervised (e.g., less educated workers in blue-collar occupations) where wages and commutes should be more strongly related (Ross and Zenou, 2008).

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.

An important result is that our reduced form static estimates diverge from the estimates including household fixed effects, and also from the estimates of the first difference equations. In other words, choices regarding the measure of the variables of interest are important, and

[18] 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).

results reflecting differences in the cross-section (i.e., *among* workers) may differ from results *within* workers and over time. Besides, this is important not only for wages and commuting, but also for the different relationships between 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 among males, between commuting and work hours among females, and between spouses' commuting times, most of which survive after controlling for household fixed effects. Contrarily, the equations in first difference suggest that changes in consumption only relate to changes in husband (but not wife) commuting, and the correlation between spouses' commuting times is no longer significant, neither the relation between commuting and hours of work.

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 husbands, as increases in housing expenditure relate to decreased commuting, and increases in the consumption of non-durables relates to increased commuting. The channel through which these correlations emerge remains 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 disappears once we exploit the longitudinal dimension of the data and estimate first difference equations. Additionally, the correlation between wages and commuting time concentrates among non-low educated workers, the occupation being mostly irrelevant, whereas the dynamic correlation between the growth rate of wages and the growth rate of commuting is mostly not significant among all types of workers. 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 complex relationships between household earnings and wealth and spouses' commuting, both in the cross-section and in the life cycle analysis. 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.

The analysis has some limitations. First of all, we could not find in the PSID data variables to instrument wages in the household context, and thus the instrumentation of the likely spurious correlation between wages and commuting is not addressed. Relatedly, the household approach often relegates wages as right-hand-side variables in the empirical analysis, against existing research in Urban Economics where wages are endogenous (e.g. Van Ommeren and Rietveld, 2005), and commuting time is the regressors. The estimates should be then interpreted as conditional correlations rather than causal relationships. Finally, statistical significance is challenging given the dimensionality of equations and sample sizes, especially in the first difference estimates of the life cycle approach. Despite these limitations, this paper opens doors for further household models incorporating commuting behaviors, as we document different correlations between consumption and spouses' commuting that reflect different complementarities between consumption, housing expenditure, and commuting time, especially in the cross-section rather than longitudinally.

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Appendices

A Log-linealization in the life cycle setting

Here we show details on the log-linealization 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:

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

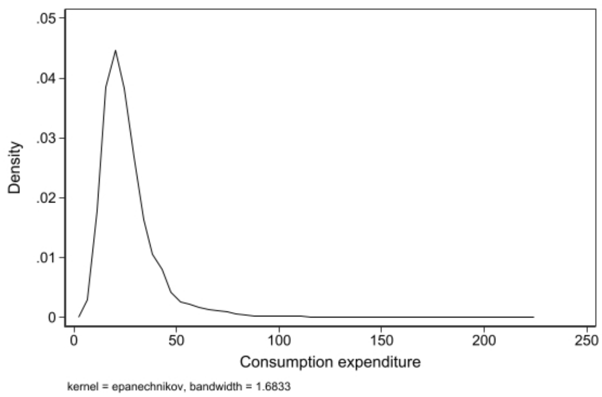
where $\phi_x^{c_1} = \dfrac{\tilde{U}_{[c_1,x]}}{\tilde{U}_{[c_1]}}\exp(-\Delta \boldsymbol{x}_t' \xi_t^{c_1})$, for each variable x of interest. Therefore, once the modeling choices on $\Delta \log \lambda_t$ and $\Delta \log(\eta_{1t} w_{1t})$ are applied, the equation characterizing husband optimal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

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

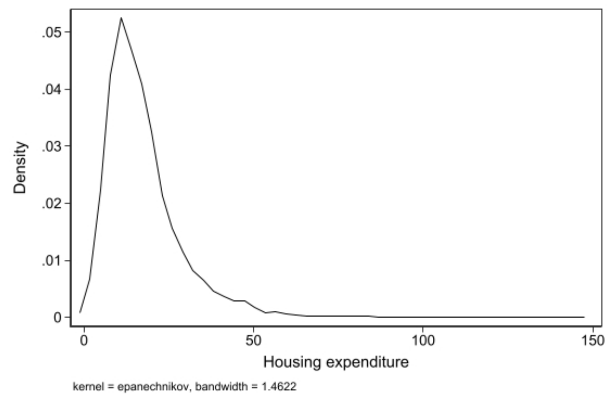
B Additional descriptives

Figure B.1: Density of key variables

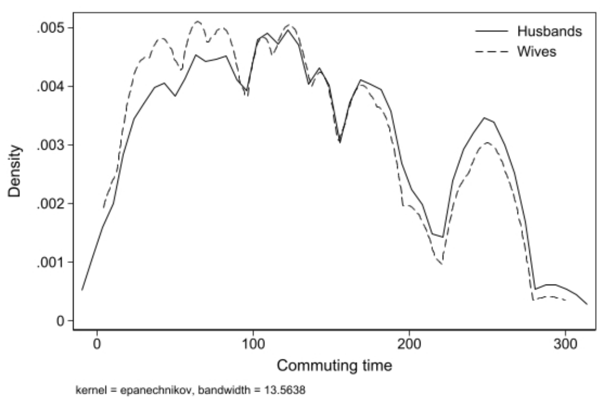
(a) Consumption expenditure (in \$1,000)



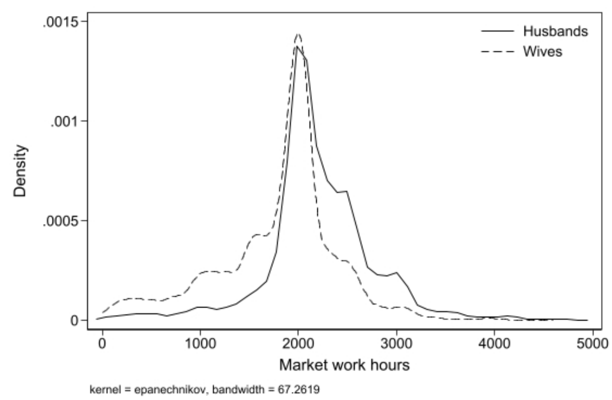
(b) Housing expenditure (in \$1,000)



(c) Commuting time (hours/year)



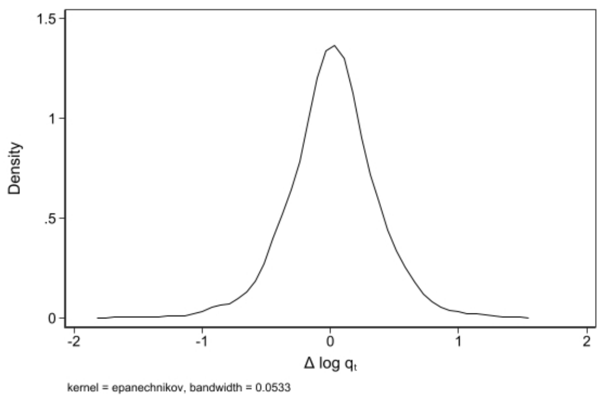
(d) Market work hours (hours/year)



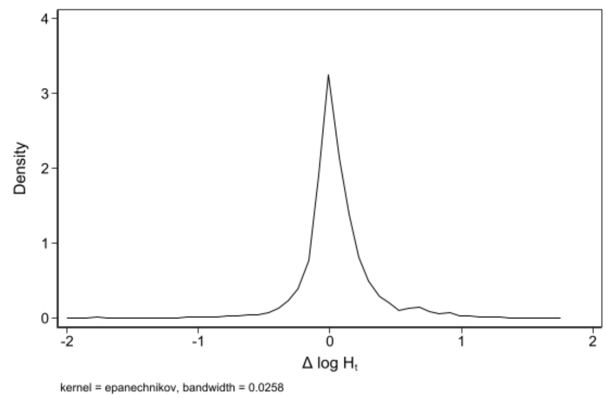
Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes.

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

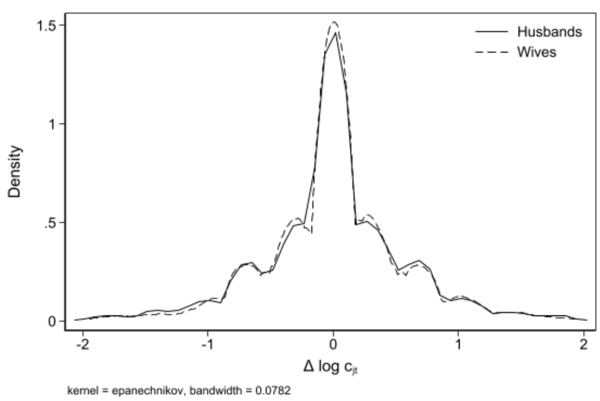
(a) Consumption expenditure (in \$1,000)



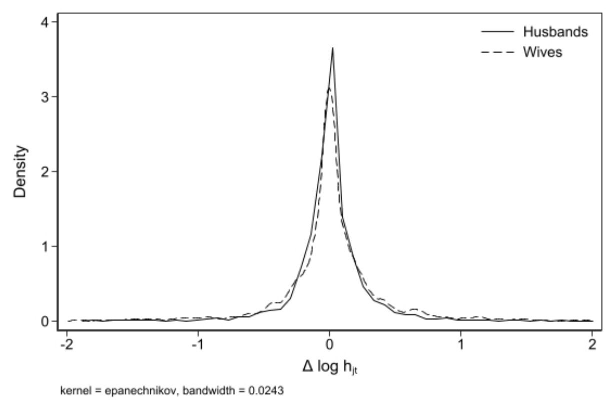
(b) Housing expenditure (in \$1,000)



(c) Commuting time (hours/year)



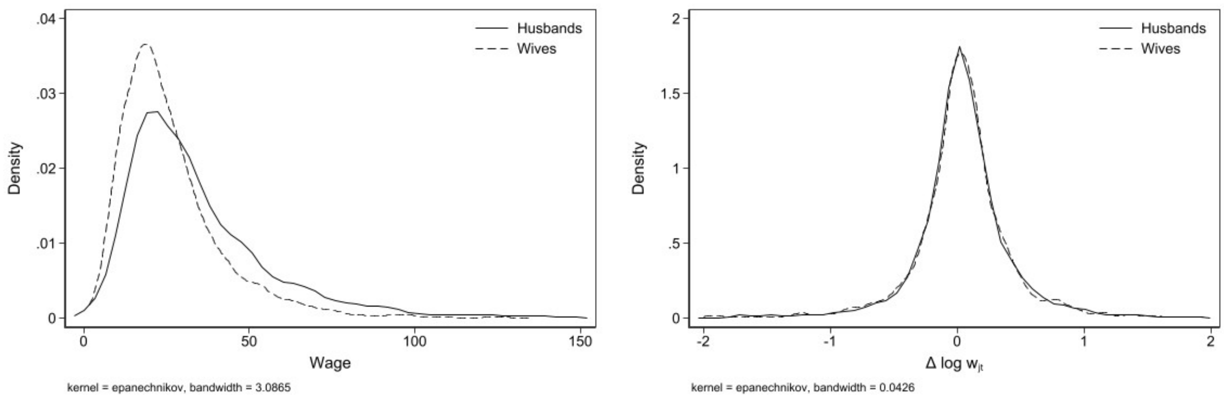
(d) Market work hours (hours/year)



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

Figure B.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 B.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×waves			4,021			
Households			1,183			

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

C Additional results

Table C.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 C.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 C.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 C.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%.