Commuting, wages, and household behavior

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Abstract

Commuting is a significant aspect of workers' daily activities that relates to several negative outcomes. The literature often models commuting from the perspective of urban models, assuming a trade-off between commuting and housing. This paper provides an alternative perspective exploring the interconnexion between couples' commuting, wages, labor supplies, and consumption within a household model. Using data from the PSID 2011-2019, the *preliminary* results show that wages and commuting exhibit cross-sectionally in a positive and highly significant correlation. However, changes in wages and changes in commuting are not related *within* individuals, i.e. in the lifecycle setting. Furthermore, commuting and labor supplies seem unrelated, whereas longer commutes relate to higher expenditures, but only cross-sectionally.

Keywords: Commuting; household behavior; wages; PSID.

JEL classification: D12; D15; J22; J31.

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1 Introduction

This paper delves into the commuting behaviors of workers within dual-earner households, exploring the interconnected dynamics between the commuting time of couples, their labor supply, and household consumption within a comprehensive household model. We meticulously derive the model's optimality conditions in both static and lifecycle frameworks and subsequently estimate household behavior using data from the Panel Study of Income Dynamics (PSID) spanning 2011-2019.

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).

In this context, the literature has acknowledged the significance of intra-household factors in commuting models. Despite that, empirical studies have predominantly concentrated on individual worker samples, often overlooking the intricacies of behaviors within the household, as the scarcity of detailed household data made it often impossible to explore household dimensions of commuting. Some exceptions include the works of Roberts et al. (2011) and De Palma et al. (2015), who analyze commuting and wellbeing, and coordinated commuting behaviors, respectuvely.

Other authors have studied worker commuting behaviors, and how they relate to other household outcomes.[1] For example, the gender gap in commuting time and distance has been thoroughly analized in the recent years, and there is consensus that men and women display different commuting behaviors, with the former commuting longer time/distance than the latter (see, e.g. Casado-Díaz et al., 2023, for a recent review). Commuting behaviors have also been linked to marital status and to the household composition. For instance, Jacob et al. (2019) found that living in couple was related to increased commuting in the UK. In the context of children, McQuaid and Chen (2012) and Neto et al. (2015) show

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

that having kids is related to increased commuting in general terms, though such a link is negative for mothers. 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).

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.

Within this framework, we first develop a household model to characterize commuting behavior, 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 hypothesize that households enjoy utility from consumption and from housing, while market work hours and commuting produce disutility. We characterize household behavior first in a static reduced form setting, and then in a lifecycle quasi-reduced form setting. By linearizing the model's optimality conditions, we derive equations for estimation and apply them to household panel data from the PSID.

The results show that, from a cross section setting, commuting and wages are positively related, as a 1% increase on wages translates into a 0.33% (0.35%) increase in male (female) commuting time. Furthermore, we also report a strong positive correlation between spouses' commuting times, and a statistically significant correlation between consumption expenditure and male, but not female, commuting time. However, the results suggest that the relationships between housing and commuting, and labor supply and commuting, are not statistically significant. On the other hand, from a lifecycle perspective, estimates suggest that *changes* in wages are not positively related to *changes* in commuting time. If anything, we find a *negative* correlation between the growth rates of wages and commuting, concentrated among low-educated males in sales and office occupations, and among high-educated females in management and professional occupations. These results suggest that there is huge heterogeneity in the static and lifecycle relationships between wages and commuting times that require further investigation. Furthermore, estimates do not support that changes in housing expenditure or in spouses' labor supplies relate to changes in commuting times. Despite that, we report positive and highly significant income effects, as family earnings do relate to spouses' commuting time growth rates.

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, labor supply, wages, housing, and consumption within households. This examination is undertaken initially in a straightforward, reduced-form context, and subsequently within a more complex lifecycle framework. Secondly, we present an empirical exploration of these interrelations, 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.

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. Sections 4 and 5 present the primary findings from the static reduced-form, and the dynamic quasi-reduced-form approaches, respectively. Section 6 discusses these results, and Section 7 concludes.

2 Model

In this section, we introduce a model that characterices 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}. 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.).[3] 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:

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

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

[3] We remain agnostic regarding the specific channels that relate commuting and wages, as we do not need to develop a fully specified model.

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 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 an important element of urban models of commuting time, namely the trade-off between housing and commuting in a monocentric city (Alonso, 1964; Mills, 1967). This 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 a recent investigations by Huai et al. (2021) and Liotta et al. (2022).

This trade-off is reflected in this household model in a different way. The household utility function explicitly assumes that workers dislike commuting and enjoy housing. Thus, households should look 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.

2.1 Maximization program and first order conditions

The household aims to maximize its utility over the 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 $U_t = \tilde{U}\left(\tilde{H}_t, \tilde{q}_t, \tilde{c}_{1t}, \tilde{c}_{2t}, \tilde{h}_{1t}, \tilde{h}_{2t}\right) = \tilde{U}_t$, where $\tilde{x} = xe^{-\boldsymbol{x}_{it}'\xi_{it}^x}$, 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]

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

2.2 Development in a static, reduced form setting

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

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

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 $x = H_t, q_t, c_{it}, h_{it},\ i \in \{1, 2\}$.

Then, the optimality conditions in a static setting can be expressed, in reduced form and for $i \in \{1, 2\}, -i \neq i$, as:

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

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

It is important to note that we do not assume separability between household consumption, labor supply, commuting, and housing. That is to say, we 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.

2.3 Development in a dynamic setting

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

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

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 as in Blundell et al. (2016) and Theloudis (2021).[5]

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

Assembling (5) and (6) together, we can obtain the equations that represent the first order conditions of program (2). As in the case of the reduced form approach, we do not assume separability.

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

2.4 Estimating equations

Modeling choices

We need to make some assumptions before we can explicitly present estimating equations, both in the reduced form and the lifecycle 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. (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 $\boldsymbol{x}_{it}^{LF}$, and wages:[6]

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

where $\eta_{it} = \eta_i(\boldsymbol{x}_{it}^{LF})$ is an unobserved function that relates 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 cotnrasts 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.

Estimating equations in static, reduced form setting

In a pure reduced form and static approach, assuming a logarithmic specification, estimating equations (4) can be expreesed, for $i \in \{1, 2\}$, and $i \neq -i$, as:

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

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

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

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

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

This formulation of estimating equations allows for the analysis of various interdependencies within the household model, reflecting the nuanced 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 often 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 lifecycle setting.

Estimating equations in a lifecycle 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, for $i \in \{1, 2\}$, and $i \neq -i$:

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

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

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

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

Deriving equations in a lifecycle settings provides additional insights to the static framework. The lifecycle 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 lifecycle 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 impact of wages on commuting is homogeneous in terms of education and occupation, or conversely depends on worker labor force characteristics. We return to this heterogeneity analysis below.

2.5 Intuition

The model incorporates key elements of traditional commuting models, such as the trade-off 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 intratemporal 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 lifecycle perspectives. The equations also allow us to examine whether the potential relationship between wages and commuting is homogenous 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, 2019). It's 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, specifically a husband and a wife (Grossbard, 2014). We select only working couples, meaning both spouses participate in the labor market and report positive 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.[7] Wages are computed as individual annual earnings divided by annual hours of work, thus providing a measure in dollars per hour. Household earnings

[7] 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.

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 (PSID, 2021).[8]

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).[9] 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.[10] 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).

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.

[8]Monetary amounts (wages, earnings, consumption, wealth) are all expressed in 2018 dollars.
[9]We define expenditure following existing research using the PSID (Theloudis, 2021; Theloudis et al., 2023).
[10]Figures B.1 and B.2 in the Appendix B show the distribution of the key variables.

Table 1: Summary statistics of key variables

Individual variables	Males ($j=1$)		Females ($j=2$)		Difference	
	Mean	St.Dev.	Mean	St.Dev.	Diff.	p value
Work hours (h_{jt})	2,206	580.9	1,798	621.3	408.4	0.000
$\Delta \log h_{jt}$	-0.001	0.379	0.016	0.546	-0.018	0.144
Hourly wage (w_{jt})	35.64	28.00	26.86	21.33	8.772	0.000
$\Delta \log w_{jt}$	0.050	0.431	0.040	0.421	0.010	0.382
Commuting (c_{jt})	191.4	162.9	160.8	130.1	30.52	0.000
$\Delta \log c_{jt}$	-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

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 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). We can easily capture worker unobservables by household fixed effects in panel data like the PSID, but the survey does not provide information for firm or residence location fixed effects. However, it does allow for the use of job changes and residence movements as instrumental variables. Therefore, we define dummy variables to identify job changes for husbands and wives, and for household residence relocations, between periods $t-1$ and t. These are used to instrument the relationship between commuting and wages at date t for each spouse in the static reduced form setting.[11]

On the other hand, instrumenting these relationships in the lifecycle setting XXX

4 Reduced form analysis

Table 2 shows the results of estimating (9) for husbands and wives. Columns (1) and (2) show GMM estimates without instrumenting the relationship between wages and commuting, whereas Columns (3) and (4) show estimates including instrumented wages. 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. Estimates on the remaining household dependent variables, as well as results for the demographics, are shown in the Appendix B.

Results show that wages and commuting are strongly related in the cross-section. Furthermore, estimates do not change when instrumenting the relationship between wages and commuting. Specifically, results indicate that a 1% increase in wages relates to an increase in commuting times of about 0.33% among husbands, and 0.35% among wives. These coefficients are statistically significant at standard levels, in line with the literature on the relationship between wages and commuting time.

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

[11] The detailed statistics of these variables are provided in Table B.1 in the Appendix B.

commuting is more sensitive to earnings.

Table 2: Reduced form results

	GMM		IV		IV & household f.e.	
Dep. var.: $\log c_{jt}$ Variables	Males $j=1$	Females $j=2$	Males $j=1$	Females $j=2$	Males $j=1$	Females $j=2$
$\log w_{jt}$	0.252***	0.322***	0.330***	0.345***	-0.245**	0.284
	(0.054)	(0.043)	(0.055)	(0.057)	(0.120)	(0.213)
$\log y_t$	-0.022	-0.168***	-0.017	-0.124**	0.050	-0.020
	(0.075)	(0.056)	(0.060)	(0.053)	(0.042)	(0.042)
$\log a_t$	-0.077***	-0.010	-0.082***	-0.015	-0.027**	0.010
	(0.015)	(0.016)	(0.015)	(0.017)	(0.012)	(0.013)
$\log H_t$	0.008	0.041	-0.014	0.027	0.089**	0.166***
	(0.040)	(0.038)	(0.040)	(0.038)	(0.039)	(0.039)
$\log q_t$	0.219***	0.065	0.205***	0.054	0.072**	0.117***
	(0.048)	(0.050)	(0.048)	(0.050)	(0.034)	(0.034)
$\log c_{-jt}$	0.316***	0.331***	0.314***	0.327***	0.360***	0.363***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.015)	(0.015)
$\log h_{1t}$	-0.014	0.009	-0.034	-0.006	-0.011	-0.062*
	(0.051)	(0.047)	(0.051)	(0.047)	(0.035)	(0.034)
$\log h_{2t}$	-0.046	0.073**	-0.046	0.057*	-0.027	0.026
	(0.031)	(0.030)	(0.029)	(0.029)	(0.022)	(0.022)
Constant	2.882***	2.782***	2.931***	2.870***	2.548***	2.218***
	(0.473)	(0.482)	(0.473)	(0.476)	(0.509)	(0.627)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Occupation f.e.	Yes	Yes	Yes	Yes	No	No
Household f.e.	No	No	No	No	Yes	Yes
Region f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	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. Housing, consumption, and hours equations are shown in Table B.2, and additional estimates are shown in Table B.3 in the Appendix B.

*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

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 $-j$'s commuting are positive statistically significant. Finally, spouses' hours of work seem not to be related to commuting times.

Intriguingly, once we net out household unobservables by including household fixed effects, most of the results hold, except the conditional correlation between commuting times and wages. Such correlation becomes negative and statistically significant for husbands, and not significant for wives. 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. Once those characteristics are net out, the correlation disappears among women, and becomes negative for husbands.

5 Results of the dynamic equations

5.1 Baseline results

Estimates of the lifecycle equation (13) are shown in Table 3, for husbands and wives. Columns (1) and (2) show GMM estimates without instrumenting the relationship between wages and commuting, whereas Columns (3) and (4) show estimates including instrumented wages. Estimates on the remaining household dependent variables, as well as results for the demographics, are shown in the Appendix B.

Overall, the results indicate that the growth rate of commuting time of spouses is relatively steady. First of all, results indicate that changes in wages do not relate to changes in commuting times, nor for husbands neither for wives. This result is 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 lifecycle 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, while high wealth is related to decreased commuting but only among wives. Changes in housing expenditure, spousal commuting time, and spouses' labor supplies seem not to be related to commuting times, as all the associated coefficients are not statistically significant at standard levels. However, changes in non-durables expenditure do relate to wives' commuting, with the association being positive and highly significant.

Table 3: Estimates of first difference equations

Dependent variable: $\Delta \log c_{jt}$	GMM		IV	
Variables	Males $j=1$	Females $j=2$	Males $j=1$	Females $j=2$
$\Delta \log w_{jt}$	-3.595	1.244	-0.872	-6.562**
	(2.777)	(2.302)	(3.801)	(3.183)
$\log y_{t-1}$	8.566***	6.290***	8.339***	6.257***
	(1.478)	(1.422)	(1.471)	(1.483)
$\Delta \log y_t$	7.810*	-1.153	3.806	0.172
	(4.733)	(2.728)	(3.498)	(2.038)
$\log a_{t-1}$	-1.219*	-1.643**	-1.214	-1.540**
	(0.721)	(0.664)	(0.761)	(0.639)
$\Delta \log a_t$	0.381	-0.870	0.363	-0.881
	(0.984)	(0.947)	(0.993)	(0.925)
$\Delta \log H_t$	-0.220*	0.311	-0.191	0.318
	(0.121)	(0.223)	(0.123)	(0.225)
$\Delta \log q_t$	0.207***	0.097	0.202***	0.124*
	(0.072)	(0.059)	(0.071)	(0.064)
$\Delta \log c_{-jt}$	0.004	0.003	0.005	0.002
	(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***	-0.215***
	(0.016)	(0.018)	(0.016)	(0.018)
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. Housing, consumption, and hours equations are shown in Table B.4, and additional estimates are shown in Table B.5 in the Appendix B.

*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

5.2 Heterogeneity

XXX

Table 4: Partial effects with heterogeneity

Partial effects on $\Delta \log c_{jt}$	Males $j = 1$	Females $j = 2$
$\Delta \log w_{jt}$ - Non-high school	-2,371***	2,694**
	(568.9)	(1,309)
$\Delta \log w_{jt}$ - High school	-26.38	59.21
	(252.7)	(654.6)
$\Delta \log w_{jt}$ - Bachelor degree	-95.87	-383.6
	(600.8)	(286.1)
$\Delta \log w_{jt}$ - Doctorate	364.0	-725.9**
	(547.1)	(335.3)
$\Delta \log w_{jt}$ - Production, transportation, other	-997.9	-249.9
	(1,054)	(708.8)
$\Delta \log w_{jt}$ - Management, professional, related	264.2	-735.4**
	(368.2)	(313.1)
$\Delta \log w_{jt}$ - Service	-831.7	188.4
	(897.3)	(712.3)
$\Delta \log w_{jt}$ - Sales, office	-1,093**	-389.5
	(524.7)	(289.7)
$\Delta \log w_{jt}$ - Natural res., construction, maintenance	-111,8	-935.8
	(691.6)	(1,371)

Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes. Partial effects evaluated at average male and female commuting times, respectively. Robust standard errors in parentheses, clustered at the household level, computed using the delta method. Point estimates shown in Table B.6 in the Appendix B.

*** significant at the 1%; ** significant at the 5%; * significant at the 10%.

6 Discussion

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7 Conclusions

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References

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.

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

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.

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.

Chidambaram, B. and J. Scheiner (2019). Understanding commuting behavior between partners. *Transportation Research Procedia 41*, 376–379.

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.

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.

Dickerson, A., A. R. Hole, and L. A. Munford (2014). The relationship between well-being and commuting revisited: Does the choice of methodology matter? *Regional Science and Urban Economics 49*, 321–329.

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.

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.

Giménez-Nadal, J. I., J. A. Molina, and J. Velilla (2023). Commuting, family, and wages. In K. F. Zimmermann (Ed.), *Handbook of Labor, Human Resources and Population Economics*, pp. 1–13. Springer.

Gottholmseder, G., K. Nowotny, G. J. Pruckner, and E. Theurl (2009). Stress perception and commuting. *Health Economics 18*(5), 559–576.

Grinza, E. and F. Rycx (2020). The impact of sickness absenteeism on firm productivity: New evidence from belgian matched employer–employee panel data. *Industrial Relations: A Journal of Economy and Society 59*(1), 150–194.

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.

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.

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.

Kahneman, D. and A. B. Krueger (2006). Developments in the measurement of subjective well-being. *Journal of Economic Perspectives 20*(1), 3–24.

Kahneman, D., A. B. Krueger, D. A. Schkade, N. Schwarz, and A. A. Stone (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science 306*(5702), 1776–1780.

Kirby, D. K. and J. P. LeSage (2009). Changes in commuting to work times over the 1990 to 2000 period. *Regional Science and Urban Economics 39*(4), 460–471.

Künn-Nelen, A. (2016). Does commuting affect health? *Health Economics 25*(8), 984–1004.

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.

Long, J. and W. Szeto (2019). Congestion and environmental toll schemes for the morning commute with heterogeneous users and parallel routes. *Transportation Research Part B: Methodological 129*, 305–333.

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. *The 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.

Oakil, A. T. M., D. Ettema, T. Arentze, and H. Timmermans (2016). Bicycle commuting in the netherlands: An analysis of modal shift and its dependence on life cycle and mobility events. *International journal of Sustainable Transportation 10*(4), 376–384.

PSID (2019). Panel study of income dynamics, public use dataset.

PSID (2021). Panel study of income dynamics main interview user manual: Release 2021.

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

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.

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.

Stutzer, A. and B. S. Frey (2008). Stress that doesn't pay: The commuting paradox. *Scandinavian Journal of Economics 110*(2), 339–366.

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 (2023). Commitment and the dynamics of household labor supply. *arXiv preprint arXiv:2307.10983*.

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 E. Gutiérrez-i Puigarnau (2011). Are workers with a long commute less productive? an empirical analysis of absenteeism. *Regional Science and Urban Economics 41*(1), 1–8.

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.

Vosough, S., A. de Palma, and R. Lindsey (2022). Pricing vehicle emissions and congestion externalities using a dynamic traffic network simulator. *Transportation Research Part A: Policy and Practice 161*, 1–24.

Appendices

A Log-linealization in the lifecycle setting

Here we show details on the log-linealization of the optimality conditions of the lifecycle 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:

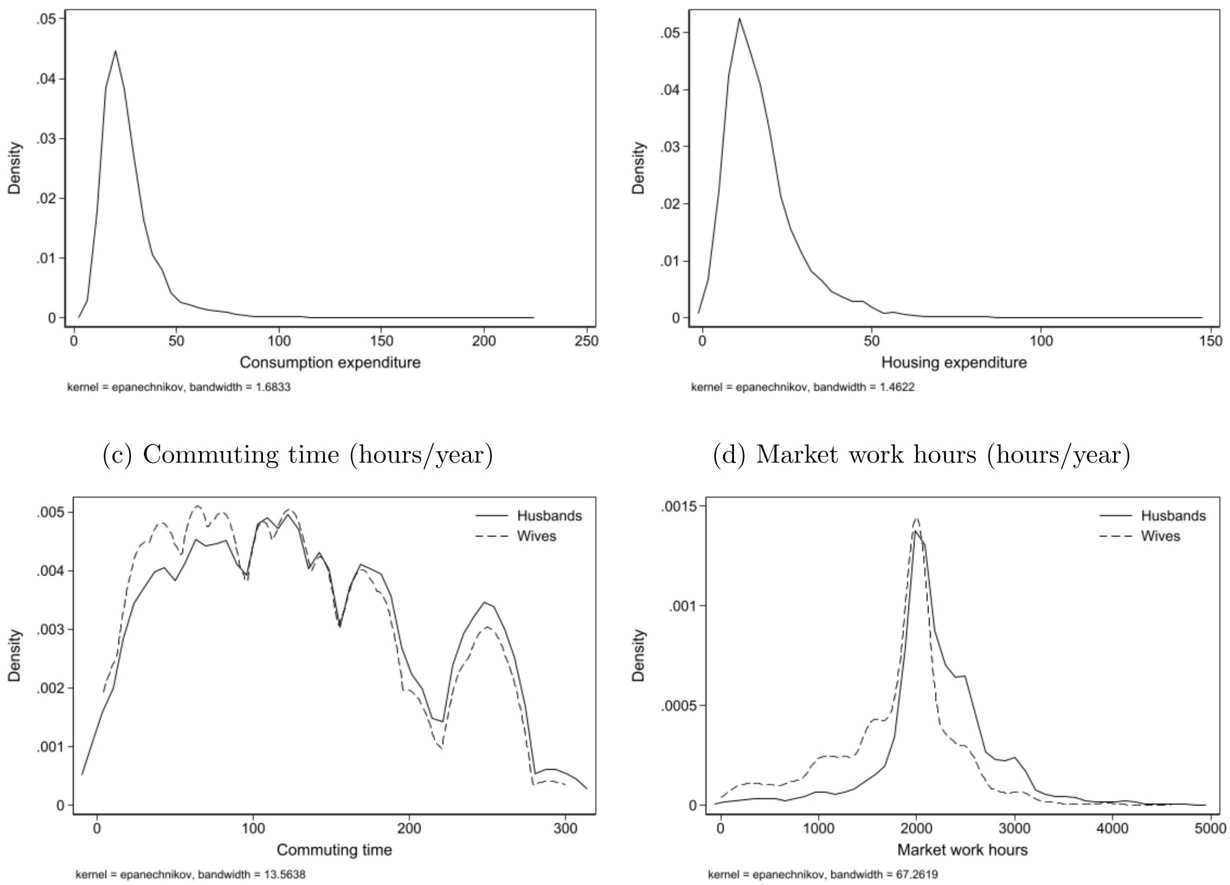
$$
\begin{aligned}
\Delta \log\left(-\tilde{U}_{[c_1]}\right) &= \phi_H^{c_1} H_{t-1} \Delta \log H_t + \phi_q^{c_1} q_{t-1} \Delta \log q_t + \phi_{c_1}^{c_1} c_{1t-1} \Delta \log c_{1t} \\
&+ \phi_{c_2}^{c_1} c_{2t-1} \Delta \log c_{2t} + \phi_{h_1}^{c_1} h_{1t-1} \Delta \log h_{1t} + \phi_{h_2}^{c_1}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

where $\phi^{c_1}_x = \frac{\tilde{U}_{[c_1,x]}}{\tilde{U}_{[c_1]}} \exp(-\Delta \boldsymbol{x}'_t \xi^{c_1}_t)$, 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:

$$
\begin{aligned}
\Delta \log c_{1t} \approx c_{1t-1} \times \Big\{ & + \underbrace{(\phi^{c_1}_{c_1})^{-1} \xi^{c_1'}_t}_{=\boldsymbol{\gamma}^{c_1}_x} \Delta \boldsymbol{x}_t \\
& + \underbrace{(\phi^{c_1}_{c_1})^{-1} \zeta_1}_{=\gamma^{c_1}_y} \log y_{t-1} + \underbrace{(\phi^{c_1}_{c_1})^{-1} \zeta_2}_{=\gamma^{c_1}_{\Delta y}} \Delta \log y_t \\
& + \underbrace{(\phi^{c_1}_{c_1})^{-1} \zeta_3}_{=\gamma^{c_1}_a} \log a_{t-1} + \underbrace{(\phi^{c_1}_{c_1})^{-1} \zeta_4}_{=\gamma^{c_1}_{\Delta a}} \Delta \log a_t \\
& + \underbrace{(\phi^{c_1}_{c_1})^{-1} \eta_{1t}}_{\equiv \eta_1} \Delta \log w_{1t} \\
& \underbrace{-(\phi^{c_1}_{c_1})^{-1} \phi^{c_1}_H}_{=\gamma^{c_1}_H} H_{t-1} \Delta \log H_t \underbrace{-(\phi^{c_1}_{c_1})^{-1} \phi^{c_1}_q}_{=\gamma^{c_1}_q} q_{t-1} \Delta \log q_t \\
& \underbrace{-(\phi^{c_1}_{c_1})^{-1} \phi^{c_1}_{c_2}}_{=\gamma^{c_1}_{c_2}} c_{2t-1} \Delta \log c_{2t} \\
& \underbrace{-(\phi^{c_1}_{c_1})^{-1} \phi^{c_1}_{h_1}}_{=\gamma^{c_1}_{h_1}} h_{1t-1} \Delta \log h_{1t} \underbrace{-(\phi^{c_1}_{c_1})^{-1} \phi^{c_1}_{h_2}}_{=\gamma^{c_1}_{h_2}} h_{2t-1} \Delta \log h_{2t} \Big\}.
\end{aligned}
$$

B Additional results

Figure B.1: Density of key variables

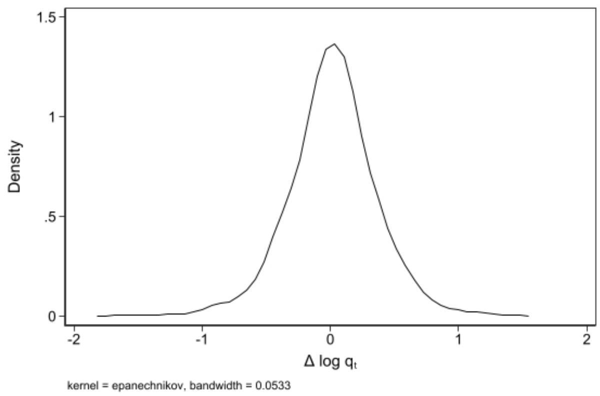


(a) Consumption expenditure (in \$1,000)
(b) Housing expenditure (in \$1,000)
(c) Commuting time (hours/year)
(d) Market work hours (hours/year)

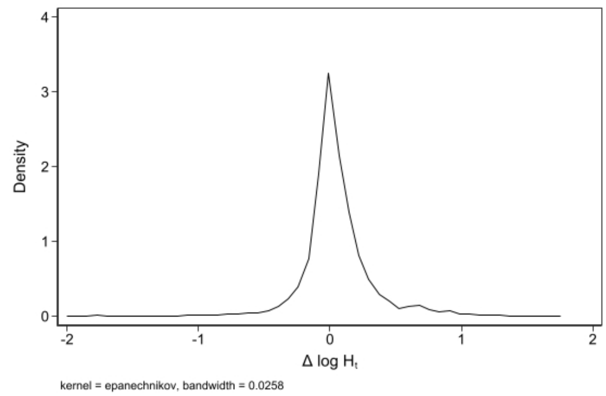
Notes: The sample (PSID 2011-2019) is restricted to two-member households who report positive labor market outcomes.

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

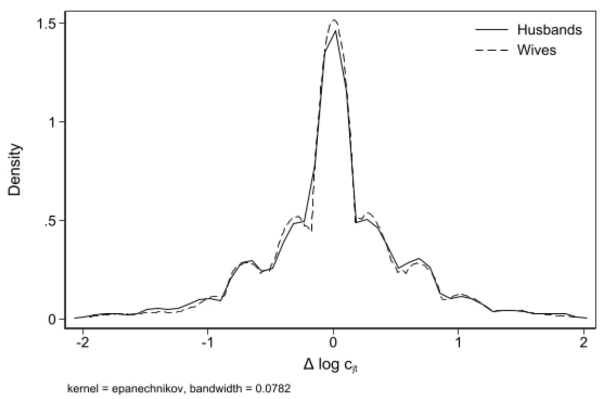
(a) Consumption expenditure (in \$1,000)



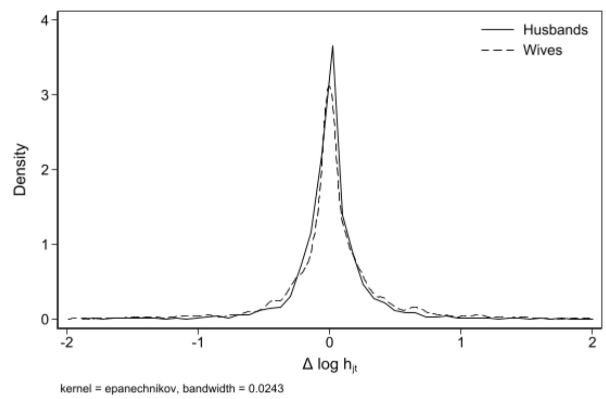
(b) Housing expenditure (in \$1,000)



(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.

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
Job change	0.158	0.365	0.185	0.388	-0.027	0.001
Household variables			Mean	St.Dev.		
Family size			3.213	1.165		
Number of children			1.012	1.129		
Moved			0.225	0.418		
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.

Table B.2: Additional reduced form results – other equations

Dependent variable:	$\log H_t$	$\log q_t$	$\log h_{1t}$	$\log h_{2t}$
$\log w_{jt}$			-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 B.3: 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 B.4: Additional first difference estimates – other equations

Dependent variable:	$\Delta \log H_t$	$\Delta \log q_t$	$\Delta \log h_{1t}$	$\Delta \log h_{2t}$
$\Delta \log w_{jt}$			-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 B.5: 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%.

Table B.6: GMM estimates on commuting with heterogeneity

	IV	
Dependent variable: $\Delta \log c_{jt}$	Males	Females
Variables	$j = 1$	$j = 2$
In terms of worker education:		
$\Delta \log w_{jt}$	-30.75***	27.47**
	(7.378)	(13.35)
$\Delta \log w_{jt} \times$ high school	30.41***	-26.56
	(7.997)	(16.50)
$\Delta \log w_{jt} \times$ Bachelor degree	29.50***	-33.08**
	(10.66)	(13.61)
$\Delta \log w_{jt} \times$ Doctorate degree	35.53***	-38.46***
	(11.08)	(13.86)
All other controls	Yes	Yes
N. observations	2,820	2,820
In terms of worker occupation:		
$\Delta \log w_{jt}$	-12.19	-4.075
	(12.88)	(11.56)
$\Delta \log w_{jt} \times$ management, professional and related	15.48	-6.8
	(13.20)	(11.95)
$\Delta \log w_{jt} \times$ service	1.369	6.924
	(18.24)	(15.51)
$\Delta \log w_{jt} \times$ sales, office	-2.440	-1.442
	(14.57)	(11.80)
$\Delta \log w_{jt} \times$ natural resources, construction, maintenance	10.58	31.62
	(15.56)	(42.58)
All other controls	Yes	Yes
N. 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. Reference category for education: non-high school. Reference category for occupation: production, transportation, other.

*** significant at the 1%; ** significant at the 5%; * significant at the 10%.