

Nonparametric Identification of Dynamic Models with Unobserved State Variables, Supplemental Material

Yingyao Hu
Johns Hopkins University

Matthew Shum
California Institute of Technology

May 2009

Abstract

We provide some additional material pertaining to our paper Hu and Shum (2008). Section 1 contains additional discussion of the identification assumptions, in the context of specific examples drawn from the empirical IO literature. Section 2 contains additional discussion of Assumption 2.

1 Additional remarks on Examples

1.1 Rust's (1987) bus engine replacement model

In addition to the two examples presented in the main paper, we present here a discussion of our assumptions in the context of a third example: Rust's (1987) bus-engine replacement model, augmented to allow for persistent unobserved state variables. In this model, $W_t = (Y_t, M_t)$, where Y_t is the indicator that the bus engine was replaced in week t , and M_t is the mileage since the last engine replacement.

As in the generalized investment example from the main text, we will restrict X_t^* to have a bounded support: for $[0, U]$ such that $0 < U < +\infty$,

$$X_t^* = 0.5X_{t-1}^* + 0.3\psi(M_{t-1}) + 0.2\nu_t; \quad \psi(M_{t-1}) = U \frac{e^{M_{t-1}} - 1}{e^{M_{t-1}} + 1}. \quad (1)$$

ν_t is a truncated standard normal shock over the interval $[0, U]$, distributed independently over t . We also assume that the initial value $X_0^* \in [0, U]$, which guarantees that $X_t^* \in [0, U]$ for all t . Hence, $X_t^* | X_{t-1}^*, Y_{t-1}, M_{t-1}$ is distributed with density determined by $f_{\nu_t}(\cdot)$.

Let $S_t \equiv (M_t, X_t^*)$ denote the persistent state variables in this model. The period utility from each choice is additive in a function of the state variables S_t , and a choice-specific non-persistent preference shock:

$$u_t = \begin{cases} u_0(S_t) + \epsilon_{0t} & \text{if } Y_t = 0 \\ u_1(S_t) + \epsilon_{1t} & \text{if } Y_t = 1 \end{cases}$$

where ϵ_{0t} and ϵ_{1t} are i.i.d. Type I Extreme Value shocks, which are independent over time, and also independent of the state variables S_t .

The choice-specific utility functions are:

$$u_0(S_t) = -c(M_t); \quad u_1(S_t) = -RC. \quad (2)$$

In the above, $c(M_t)$ denotes the maintenance cost function, which is increasing in mileage M_t , and $0 < RC < +\infty$ denotes the cost of replacing the engine. We also assume that the maintenance cost function $c(\cdot)$ is bounded below and above: $c(0) = 0$; $\lim_{M \rightarrow +\infty} c(M) = \bar{c} < +\infty$. Mileage evolves as:

$$M_{t+1} - (1 - Y_t)M_t = \exp(\eta_{t+1} + X_{t+1}^*). \quad (3)$$

where $\eta_{t+1} > 0$ follows a standard normal random variable, truncated to $[0, 1]$, with density $\tilde{\phi}(\eta) \equiv \frac{\phi(\eta)}{\Phi(1) - \Phi(0)}$, where ϕ and Φ denote the standard normal density and CDF.¹ Hence, X_t^* affects the evolution of mileage, but not the agent's utilities. Furthermore, following Rust's assumptions, previous mileage M_{t-1} has no direct effect on current mileage M_t when the engine was replaced in the previous period ($Y_{t-1} = 1$). ■

This is a stationary dynamic optimization models, in which the conditional choice probabilities take the multinomial logit form (for $Y_t = 0, 1$): $P(Y_t|S_t) = \exp(V_{Y_t}(S_t)) / \left[\sum_{y=0}^1 \exp(V_y(S_t)) \right]$ where $V_y(S_t)$ is the choice-specific value function in period t , defined recursively by $V_y(S_t) = u_y(S_t) + \beta E \left[\log \left\{ \sum_{y'=0}^1 \exp(V_{y'}(S_{t+1})) \right\} | Y_t = y, S_t \right]$. We consider each assumption in turn.

Assumption 1 is satisfied for this model.

Assumption 2 contains three invertibility assumptions. For the V_t variables in Assumption 2, we use $V_t = M_t$, for all periods t . As in the generalized investment example, we begin by verifying Lemma 4 from the main text, which has a necessary condition for an operator to be one-to-one. For convenience, we reproduce that Lemma here:

¹For this to be reasonable, assume that mileage is measured in units of 10,000 miles.

Lemma 4 (Necessary conditions for one-to-one): If L_{R_1, R_3} is one-to-one, then for any set $\mathcal{S}_3 \subseteq \mathcal{R}_3$ with $\Pr(\mathcal{S}_3) > 0$, there exists a set $\mathcal{S}_1 \subseteq \mathcal{R}_1$ such that $\Pr(\mathcal{S}_1) > 0$ and

$$\frac{\partial}{\partial r_3} f_{R_1, R_3}(r_1, r_3) \neq 0 \text{ almost surely for } \forall r_1 \in \mathcal{S}_1, \forall r_3 \in \mathcal{S}_3. \quad (4)$$

Proof: in Appendix of Hu and Shum (2008).

We first consider Assumption 2(i). Pick any w_t . Because X_t^* directly enters the mileage process, the distribution of M_{t+1} depends on X_{t+1}^* . Similarly, the distribution of M_{t-2} depends on X_{t-2}^* . Since (X_{t+1}^*, X_{t-2}^*) are correlated, the density of $(M_{t+1}, w_t, w_{t-1}, M_{t-2})$ varies in M_{t-2} , for different values of (M_{t+1}, w_t, w_{t-1}) . The discussion of Assumption 2(iii) is very similar to that of 2(i), and we omit it for convenience here.

Assumption 2(ii) requires that, for all w_t , the mapping $L_{M_{t+1}|w_t, X_t^*}$ is one-to-one. As before, for any w_t , M_{t+1} is distributed according to a mixture distribution which depends on X_{t+1}^* . Since X_{t+1}^* and X_t^* are serially correlated, M_{t+1} will vary in X_t^* , for fixed w_t .

Here we have just shown that necessary conditions for Assumption 2 hold in this example. However, because the laws of motion (1) and (3) are both either linear or log-linear, we can also verify sufficient conditions for Assumption 2, as we did in Appendix B in the main paper, for the generalized investment example. Since the arguments are very similar to that example, we do not repeat them here.

Assumption 3 contains two restrictions on the density $f_{W_t|W_{t-1}, X_t^*}$, which factors as

$$f_{W_t|W_{t-1}, X_t^*} = f_{Y_t|M_t, X_t^*} \cdot f_{M_t|Y_{t-1}, M_{t-1}, X_t^*}. \quad (5)$$

Assumption 3(i) requires that, for any (w_t, w_{t-1}) , this density is bounded between 0 and $+\infty$. The first term is the CCP $f_{Y_t|M_t, X_t^*}$, which is a logit probability. Because the per-period utilities, net of the ϵ 's, are bounded away from $-\infty$ and $+\infty$, the logit choice probabilities are also bounded away from zero. The second term is the mileage law of motion $f_{M_t|Y_{t-1}, M_{t-1}, X_t^*}$ which, by assumption, is a truncated normal distribution, so it is also bounded away from zero and $+\infty$. The bounded support assumption on M_t is crucial but, in practice, imply little loss in generality, because typically in estimating these models, one can take the upper and lower bounds on M_t from the observed data.

Assumption 3(ii) ensures that the eigenvalues in the decomposition (Eq. (12) in the main paper) are distinctive. Because of the factorization (5), and the fact that the CCP's

are bounded away from zero, a sufficient condition for Eq. (3) in the main paper is that

$$\frac{\partial^2}{\partial m_t \partial m_{t-1}} \ln f_{M_t|Y_{t-1}, M_{t-1}, X_t^*}(m_t|y_{t-1}, m_{t-1}, x_t^*) \quad (6)$$

is strictly monotonic in x_t^* , for all m_t , x_t^* , and some $w_{t-1} = (y_{t-1}, m_{t-1})$.

For any value of m_t , pick any m_{t-1} such that $y_{t-1} = 0$ (ie., the bus engine was not replaced in period $t - 1$). The density of $M_t|Y_{t-1}, M_{t-1}, X_t^*$ for this pair of (m_t, m_{t-1}) , is distributed with density $\tilde{\phi}\left(\log\left(\frac{m_t - m_{t-1}}{\exp(x_t^*)}\right)\right) / [m_t - m_{t-1}]$ on the range $m_t \in [m_{t-1}, m_{t-1} + \exp(x_t^*)]$, where $\tilde{\phi}(\cdot)$ denotes a truncated standard normal density. The second derivative of the log of this density is monotonic in x_t^* .

Assumption 4 presumes a known functional G such that $G\left[f_{M_{t+1}|Y_t, M_t, X_t^*}(\cdot|y_t, m_t, x_t^*)\right]$ is monotonic in x_t^* . Eqs. (1) and (3) imply that

$$M_{t+1} = (1 - Y_t)M_t + \exp(\eta_{t+1} + 0.2\nu_{t+1}) \cdot \exp(0.3\psi(M_t)) \cdot \exp(0.5X_t^*). \quad (7)$$

Let C_{med} denote the median of the random variable $\exp(\eta_{t+1} + 0.2\nu_{t+1})$, which is a truncated log-normal random variable. Then

$$\text{med}\left[f_{M_{t+1}|Y_t, M_t, X_t^*}(\cdot|y_t, m_t, x_t^*)\right] = (1 - y_t)m_t + C_{med} \cdot \exp(0.3\psi(m_t)) \cdot \exp(0.5x_t^*)$$

which is monotonic in x_t^* . Hence, we can pin down $x_t^* = \text{med}\left[f_{M_{t+1}|Y_t, M_t, X_t^*}(\cdot|y_t, m_t, x_t^*)\right]$.

1.2 Remark on investment models

For Example 2 in the main paper, we considered a general investment model in the framework of Doraszelski and Pakes (2007). There is a recent and growing empirical literature based on these types of dynamic models, including Collard-Wexler (2006), Ryan (2006), and Dunne, Klimer, Roberts, and Xu (2006). Pakes (2008, section 3) and Ackenberg, Benkard, Berry, and Pakes (2007) discuss additional examples.

On the other hand, the productivity literature has by and large been based on the “pure” investment model, typified by Olley and Pakes (1996) (OP). This model differs in an important way from the types of models considered in our paper. Namely, in OP, capital stock (corresponding to the M variable in Example 2) evolves deterministically, conditional on the previous period’s capital (M_{t-1}) and investment (Y_{t-1}). This feature violates two of our maintained assumptions ($\# 2,3$), which require that M_t depend on X_t^* even conditional

on (Y_{t-1}, M_{t-1}) . For this reason, in Example 2 in the main paper, we do not consider the “pure” investment model as in OP, but rather a generalized investment model in which M_t does not evolve deterministically.

2 Further discussion on Assumption 2

In this section we discuss how Assumption 2 is used to ensure the validity of two different ways for taking operator inverses. Consider two scenarios involving an operator equation

$$L_{R_1, r_2, R_4} = L_{R_1 | r_2, R_3} L_{r_2, R_3, R_4}. \quad (8)$$

In the first scenario, suppose we want to solve for L_{r_2, R_3, R_4} given L_{R_1, r_2, R_4} and $L_{R_1 | r_2, R_3}$. The assumption that $L_{R_1 | r_2, R_3}$ is one-to-one guarantees that we may have

$$L_{R_1 | r_2, R_3}^{-1} L_{R_1, r_2, R_4} = L_{r_2, R_3, R_4}. \quad (9)$$

As an example, Assumption 2(ii) guarantees that pre-multiplication by the inverse operator $L_{V_{t+1} | w_t, X_t^*}$ is valid, which is used in the equation following Eq. (9).

In the second scenario, suppose we need to solve for $L_{R_1 | r_2, R_3}$ given L_{R_1, r_2, R_4} and L_{r_2, R_3, R_4} in equation (8). We would need the operator L_{r_2, R_3, R_4} to be invertible as follows:

$$L_{R_1, r_2, R_4} L_{r_2, R_3, R_4}^{-1} = L_{R_1 | r_2, R_3}. \quad (10)$$

As proved in Lemma 1 in Hu and Schennach (2008), the sufficient condition for obtaining Eq. (10) from Eq. (8) is that the operator L_{R_4, R_3, r_2} is one-to-one.² (Notice that the operator L_{R_4, R_3, r_2} is from $L^p(\mathcal{R}_3)$ to $L^p(\mathcal{R}_4)$.)

Assumption 2(i) is an example of this. It is used to justify the post-multiplication by $L_{V_{t+1}, \bar{w}_t | w_{t-1}, V_{t-2}}^{-1}$ and $L_{V_{t+1}, w_t | \bar{w}_{t-1}, V_{t-2}}^{-1}$ in, respectively, Eqs. (10) and (11). Similarly, Assumption 2(iii) guarantees that post-multiplication by $L_{V_t | w_{t-1}, V_{t-2}}^{-1}$, which is used in the second line of the bottom display on pg. 21. Throughout this paper, we only post-multiply by the inverses of $L_{V_{t+1}, w_t | w_{t-1}, V_{t-2}}$ and $L_{V_t | w_{t-1}, V_{t-2}}$; all other cases of inverses involve pre-multiplication. For a more technical discussion, see Aubin (2000, sections 4.5-4.6).

²A similar assumption is also used in Carroll, Chen, and Hu (2009).

References

- ACKERBERG, D., L. BENKARD, S. BERRY, AND A. PAKES (2007): “Econometric Tools for Analyzing Market Outcomes,” in *Handbook of Econometrics, Vol. 6A*, ed. by J. Heckman, and E. Leamer. North-Holland.
- AUBIN, J.-P. (2000): *Applied Functional Analysis*. Wiley-Interscience.
- CARROLL, R., X. CHEN, AND Y. HU (2009): “Identification and estimation of nonlinear models using two samples with nonclassical measurement errors,” *Journal of Nonparametric Statistics*, forthcoming.
- COLLARD-WEXLER, A. (2006): “Demand Fluctuations and Plant Turnover in the Ready-to-Mix Concrete Industry,” manuscript, New York University.
- DORASZELSKI, U., AND A. PAKES (2007): “A Framework for Dynamic Analysis in IO,” in *Handbook of Industrial Organization, Vol. 3*, ed. by M. Armstrong, and R. Porter, chap. 30. North-Holland.
- DUNNE, T., S. KLIMER, M. ROBERTS, AND D. XU (2006): “Entry and Exit in Geographic Markets,” manuscript, Penn State University.
- HU, Y., AND S. SCHENNACH (2008): “Instrumental variable treatment of nonclassical measurement error models,” *Econometrica*, 76, 195–216.
- HU, Y., AND M. SHUM (2008): “Nonparametric Identification of Dynamic Models with Unobserved State Variables,” Johns Hopkins University, Dept. of Economics working paper #543.
- OLLEY, S., AND A. PAKES (1996): “The Dynamics of Productivity in the Telecommunications Equipment Industry,” *Econometrica*, 64, 1263–1297.
- PAKES, A. (2008): “Theory and Empirical Work in Imperfectly Competitive Markets,” Fisher-Schultz Lecture at 2005 Econometric Society World Congress (London, England).
- RUST, J. (1987): “Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher,” *Econometrica*, 55, 999–1033.
- RYAN, S. (2006): “The Costs of Environmental Regulation in a Concentrated Industry,” manuscript, MIT.