What Have We Learned from Structural Models?

By RICHARD BLUNDELL[*]

At a broad level a structural economic model is one where the *structure* of *decision making* is fully incorporated in the specification of the model. By identifying the 'deep' parameters that describe preferences(technologies) and constraints of the decision-making process, structural models are able to provide counterfactual predictions. In turn they uncover the mechanisms that underpin observed behaviour. Their ability to provide counterfactual policy predictions sets structural models apart from reduced-form models. But structural models require the detailed specification of the decision-making problem - the constraints and the preferences. This will typically place tougher requirements on measurement and rely, in part, on stronger assumptions.

As a running example I will use the empirical microeconomic analysis of labor supply and consumer behavior, with some discussion of human capital models. These are areas where much has been learned and where there are a wide spectrum of well-formulated questions from the ex-post impact of past changes in prices, wages and taxes on behaviour, through to the analysis of counterfactual policy changes and optimal design. These areas also have well developed applications in static choice *and* dynamic choice.

The focus throughout is on studies that allow a better understanding of the mechanisms underlying observed behaviour and provide reliable insights about policy counterfactuals. Emphasis is given to models that minimize assumptions on the *structural function* and on *unobserved heterogeneity*. Dynamic structural models face stronger requirements for identification but also hold out the greatest potential for structural analysis. Quasi-structural models, which focus on a subset of structural parameters and/or mechanisms rather than conducting full counterfactuals, can be used to assess some of the full model assumptions. Similarly the alignment of moments from structural and 'reduced form' approaches is informative about the reliability of the structural model specification.

There are other key fields in empirical microeconomics where both dynamic and static structural analysis, have provided, and continue to provide, key new insights. Perhaps the most clear-cut are in industrial organisation. Structural models of auctions and of market structure have allowed the analysis of counterfactuals that have been central to understanding and improving market design across a wide range of applications, Haile and Tamer (2003), Ciliberto and Tamer (2009) and Crawford and Yurukoglu (2015) are key examples. The use of equilibrium concepts to deliver identification is one of the importance insights from this literature. The structural analysis of networks and of labor market search develops this line of research, see de Paula (2016) and Postel-Vinay and Robin (2002) respectively. I will touch on these fields, but in much less detail than they deserve.

The next section lays out some of the key requirements on empirical models for the analysis of policy reform. The idea is to place structural modeling center ground in empirical policy research. The study of counterfactual policy reform and optimal policy design is among the most demanding in empirical microeconomics often leaning very heavily on structural assumptions. Section II examines static structural models of choice in more detail drawing out some of the successes, particularly where constraints are carefully specified and identification is clearly argued. This leads on to dynamic choice models which, used for this purpose. I argue, have the greatest potential for delivering new insights on behaviour and policy reform. In Section III 'full-structural' dynamic models are distinguished from 'quasi-structural' models. Finally,

[*] University College London and Institute for Fiscal Studies, r.blundell@ucl.ac.uk. Acknowledgements: I am grateful to Orazio Attanasio, Michael Keane, Costas Meghir and Ariel Pakes for helpful discussions on related material. This research is part of the ESRC Centre for the Microeconomic Analysis of Public Policy at IFS, I would like to thank the ESRC for their support, I am also grateful to the ERC under project MicroConLab for financial support.

before concluding, Section IV reflects on the growing application of nonparametric revealed preference which uses shape restrictions from the structure of economic optimisation to deliver (bounds on) counterfactual predictions under minimal incidental assumptions.

I. Structural Models and Policy Design

What is the role of structural models in empirical policy design? One way to answer this is to lay out the steps involved in assembling the foundations of empirical policy analysis. Using the Mirrlees Review of tax reform as an example, see Blundell (2012), I identify the following five steps: (i) Uncovering the key margins of adjustment; (ii) Measuring effective incentives; (iii) Understanding the importance of information and complexity; (iv) Estimating behavioral responses; and (v) Counterfactual policy simulation and optimal design. Structural models enter into steps (iv) and (v) but steps (i) - (iii) are also essential for a wel-specified structural model.

Step (i) examines the margins of labour market adjustment, for example, that may be useful for tax policy analysis. Blundell, Bozio and Laroque (2011) point to the importance of a lifetime view of employment and hours differentiated along the extensive and intensive margins and accentuated at particular ages for different education groups. There is higher attachment to the labor market for higher educated where career length matters. Wages grow stronger and longer over the lifetime for higher educated human capital profiles in work appear to be complementary to education investments. These are the descriptive statistics that underpin any structural analysis.

Next comes step two, the measurement of effective incentives. An advantage of structural models is the requirement for a precise statement of constraints. In the tax and welfare reform area this requires a detailed institutional knowledge of overlapping taxes, tax-credits and welfare benefits. As Mirrlees et al (2011) and Moffitt (2016) show all too clearly, the tax and welfare benefit system, taken together, is complex with many overlapping benefits and taxes. If we are to recover preferences accurately we have to understand the salience of the various tax and welfare benefit incentives. This is step three and requires a careful modeling of welfare programme participation among eligible families.

It is only after having built up a clear picture from these first three steps that the rigorous econometric analysis of structure comes into play. At this stage an eclectic mix of reduced form and structural approaches seems appropriate. There is a strong complementarity between approaches. Quasi-experimental evaluations can provide robust measures of certain policy impacts but are necessarily local and limited in scope. Structural estimation, based on revealed preference models of choice, allow counterfactual policy simulations which can then feed into a policy (re-)design analysis in step five. But structural models require careful measurement, for example accurately specifying effective tax rates (step 2), and careful modeling of preferences, for example the specification of stigma costs (step 3).

Structural models, or certain aspects of them, can be validated using evidence from experimental and quasi-experimental contrasts. For example, a well designed experiment can recover certain structural parameters. Similarly, the policy impact (treatment) parameter identified in by quasi-experiment (e.g. from differences-in-differences) can be simulated in the structural model and the two compared. I return to this below.

II. Static Discrete Choice Labor Supply Models

Maintaining the running example of the empirical microeconomic analysis policy reform, this section focusses on static structural discrete choice models of labor supply and programme participation. These have been the workhorse of empirical analysis of welfare-benefit reform. The plethora of welfare and tax proposals and actual reforms that surfaced in the late 1980s and 1990s in the UK and the US gave new impetus to the development of structural models. These models incorporated choices not only over part-time and full-time work but also over different welfare and tax credit programs, incorporating stigma costs and the complicated non-linear budget constraints that reflected the overlap of the many welfare programs, tax-credits and personal taxes.

In the US these models were used to assess the impact of means-tested programs and potential reforms to them, while in the UK they were used to assess welfare-benefit reform, especially the extension of tax-credits, see Blundell and Hoynes (2004). Policy counterfactuals were required as these reform proposals involved non-marginal changes to the tax-credit and welfare system and were directly aimed at changing welfare participation and labor supply.

These policies were directed at relatively poor families with low labor market attachment and low earnings. The key elements of a structural model for low income families, see Keane and Moffitt (1998), involve a precise definition of the budget constraint, with all the tax/tax-credit and benefit interactions. The specification of preferences over different hours and programme options that give rise to multinomial choice model across discrete hours and welfare combinations. Heterogeneity is essential reflecting observed differences across families through measured demographics, and unobservable differences in 'tastes' for work, stigma costs, child-care costs and fixed costs of work.

These models performed well, their ex-ante predictions matching post-reform behavior, see Blundell (2012). Identification was based on a convincing sources of plausibly exogenous variation in welfare and tax rules across time and locations. The models also proved invaluable for counterfactual evaluations of the impact of alternative policies and have been used to examine optimal design, see Blundell and Shephard (2012). They provided precisely estimated wage and income elasticities at the extensive and intensive margins across different demographic groups. Extensive responses being more elastic for low educated mothers with young children. This provided a secure basis for targeting earned income tax expansions toward low income families. Complexity and overlapping benefit withdrawal rates were found to be clearly inefficient and inhibited take-up, providing a clear motivation for the integration of benefits and tax credits, see Brewer, Saez and Shephard (2011).

Nonetheless, there remain many areas where these structural models are in need of further refinement, one area is to allow for restrictions on choices. Here work on identifying consideration sets using revealed reference conditions holds out some hope, see Beffy et al (2015). Moreover, the models discussed so far only allow for limited, if any, dynamic behaviour. Human capital investment, persistent wage shocks, and search frictions add potentially valuable dynamics considerations. To evaluate the importance of these we consider, in the next section, to dynamic structural models.

Before turning to dynamics though it is worth briefly highlighting some recent quasi-structural studies that, rather than trying to identify full individual counter-factual simulations, seek to relax the assumptions on preferences and use only the restrictions from revealed preference to identify some key parameters of interest. For example, Blomquist et al (2014) show how to non-parametrically estimate the conditional mean of taxable income imposing all the revealed preference restrictions of utility maximization and allowing for measurement errors. This work aims at a robust measure of the taxable income elasticity rather than identifying the full structure of the optimisation problem. Manski (2014) develops a basic revealed preference analysis assuming only that persons facing piece-wise linear constraints prefer more income and leisure. He then shows that, assuming groups of persons who face different choice sets have the same preference distribution, partial prediction of tax revenue under proposed policies and partial knowledge of the welfare function for utilitarian policy evaluation is feasible.

I return to the general use of nonparametric revealed preference in the structural analysis of individual decisions in section IV.

III. Dynamic Models of Choice

Identification of structural models of choice in a dynamic optimising environment requires placing strong assumptions on subjective discount rates and the distribution of beliefs. For example, building on the original work by Rust (1994), Magnac and Thesmar (2002) show that in discrete choice settings the utility functions in each alternative cannot be (non-parametrically) identified without external information on the distribution function of unobserved preference shocks, the discount rate, and the current and future preferences in one (reference) alternative (Arcidiacono and Miller 2011). Norets and Tang (2014) provide conditions for identifying the probability distribution of the choice specific disturbance in stationary binary choice environment in the presence of exclusion restrictions on a set of variables that affect the transitions but not the utility itself. Fang and Wang (2015) have recently extended these results in important ways to examine structural models that permit time-inconsistent behavior.

The upshot of these results is that particular care needs to be taken in specifying, estimating and validating dynamic models. One reaction is to focus on a subset of structural parameters that are more robustly identified. One can view this as a 'partial' or 'quasi' structural approach to dynamic models. For example, one may estimate 'life-cycle' consistent preferences by conditioning on consumption (or saving), see Blundell and Walker (1986). Another example is the partial insurance literature, see Blundell, Preston and Pistaferri (2008). Below I comment further on these, and other related examples, where subsets of structural parameters are the focus of interest.

As they stand, none of these quasi-structural approaches are robust to intertemporal non-separability as in models that incorporate human capital decisions alongside labor supply and consumption choices. For this we need a more fully specified life-cycle model and it is to these structural models that we turn first.

A. Fully Specified Structural Dynamic Models

The ground-breaking work in the development of structural models of life-cycle labor supply choices was carried out by Heckman and MaCurdy (1980), subsequently developed for discrete choice decisions and integrated with human capital choices by Keane and Wolpin (1997) among others. That work uncovered key differences between short-run and longer run responses to wage changes and found that, once human capital choices are incorporated, estimated labor supply responses from static models can be quite misleading. We will also see that the assumptions underlying standard quasi-experimental approaches are also rendered invalid in these dynamic settings.

Maintaining the running theme of the analysis of tax and welfare reform, we might ask how interactions between education decisions, work experience dynamics and labour supply should be accounted for in the evaluation and design of tax and welfare systems? Why did static structural models of labor supply and welfare participation, discussed in the previous section, perform well?

Once we are in a dynamic setting, structural models not only require us to specify preferences and constraints over income and leisure they also require a description of beliefs, of credit markets, of risk preferences and of uncertainty. The reward for this is that they provide at counterfactuals across the life-cycle and also identify the 'insurance value' of redistributive policies, measuring the trade-off between insurance and incentives. As the recent work of Stantcheva (2015) and Golosov and Tsyvinski (2015) has shown, the theory of tax design is changed in important ways by the insights from these dynamic models. Structural models also pinpoint the distinction between heterogeneity and state dependence, central to counterfactual policy predictions and for understanding the welfare costs of policy interventions.

To bring some substance to this discussion I will draw on the Blundell et al (2016) [BDMS] study of female labor supply, human capital and tax reform. The systematic reforms to the tax, tax credit and welfare system in the UK over the two decades from the early 1990s provide an almost ideal setting for dynamic structural analysis. There is significant variation in incentives deriving from a sequence of reforms involving changes in the generosity of the welfare and earned income tax credit system for families with children. There is also availability of longitudinal data that track changes in labor supply and human capital over this period with detailed measures of income, assets, life-histories, and family composition.

A motivation for the policy reforms was that by incentivising women into work, even when they have young children, will preserve their labour market attachment and reduce skill depreciation. The BDMS study aimed to uncover how reforms to the tax, tax-credit and welfare benefit system affect education choices, experience capital accumulation, employment and hours of work over the life-cycle. To examine human capital choices and to separate experience effects from individual heterogeneity and external shocks requires a structural approach. The sequence of tax, tax credit, welfare benefit and tuition reforms for make identification more transparent. By conditioning on life-history and family background variables reduces the strength of conditional independence assumptions on unobserved heterogeneity. Estimation is by the method of simulated moments. By comparing model counterfactuals with quasi-experimental (difference-in-difference) contrasts for specific ex-post reforms BDMS provide another source of model validity.

The structural model describes life-cycle decisions in three stages, starting with schooling choices, then the labour supply, labor market experience and consumption choices, and finally retirement decisions. The recent structural model by Fan, Sheshadri and Taber (2015) has highlighted the importance of interactions between human capital investments and retirement.

Education decisions follow a discrete choice model with risk averse preferences over future uncertain earnings and family composition. The model allows for borrowing constraints, tuition costs and student loans. Choices are made conditional factors formed of many family background variables at age 16, including parental education/occupation, financial circumstances, siblings, region of birth, and books in the home.

Once schooling is complete, consumption and labor supply (part-time or full-time work) are chosen over the life-cycle subject to the budget constraint that accounts for taxes, benefits and childcare costs. A net worth liquidity constraint is imposed on an otherwise standard intertemporal budget constraint. Preferences over work depend on family composition, education, partner, partner labour supply, background factors, and unobserved heterogeneity.

Family formation, fertility and partnering also have to be modeled in a full structural dynamic model. In the BDMS study they are treated as a (weakly) exogenous dependent on past demographics and completed levels of schooling. Partners employment and earnings are uncertain and depend on his education and on whether he worked in the previous period.

A key part of the structural model is the wage equation in which log hourly wages for woman'i', age 't', in each birth cohort; with school level 's', experience 'e', and labour supply 'l' are given by:

$$\ln w_{sit} = \ln W_{sit} + \gamma_{si} \ln (e_{sit} + 1) + \upsilon_{sit} + \xi_{sit}$$

$$\upsilon_{sit} = \rho_s \upsilon_{sit-1} + \mu_{sit}$$

$$e_{sit} = e_{sit-1} (1 - \delta_s) + g_s (l_{sit})$$

where γ_{si} varies with schooling level s and background factors x_i. Allowing a concave profile for experience effects that differ by schooling level and background factors. υ_{sit} is a persistent external shock to wages, correlated with initial conditions. ξ_{sit} is a transitory shock. Experience capital e evolves with depreciation δ and additions to experience $g_s(l_{sit})$ set to unity for full-time $g_s(FT) = 1$. The part-time experience value $g_s(PT)$ is estimated. δ_s depreciation of human capital δ_s gives a cost of not working and differs, as do all other parameters, by schooling level.

Figure 1 plots average hourly wages among working women in the data and the corresponding structural model counterfactual simulation by the three education groups - basic (sec), high school (HS) and 3 year college completors (univ). The model fit is good (for labor supply and education choices too) but it turns out this is only achieved by allowing the experience returns γ_{si} to differ by education level s and part-time work to have a freely estimated parameter g_s in the production of experience capital. The estimated experience effects for earnings display strong *dynamic complementarity* with education. Moreover, there are *significantly lower experience effects for those in part-time work.* Experience effects and the part-time penalty are shown to explain 70% gender gap in wages.

For lower educated women, once depreciation and part-time work are accounted for, experience effects on wages are very small. Quite the opposite for high educated women. These results neatly explain the alignment of structural and quasi-experimental results from static discrete choice models referred to above. With minimal experience effects, static models that account for nonlinearity in the budget set, childcare costs and differences in family structure can explain part-time and full-time work for women with low levels of education quite well. The structural model estimates also find that lower education women with children have more elastic labour supply at the extensive margin and larger income effects.

For higher educated women, experience capital is key to explaining the steep wage profiles followed by a severe flattening of the profile

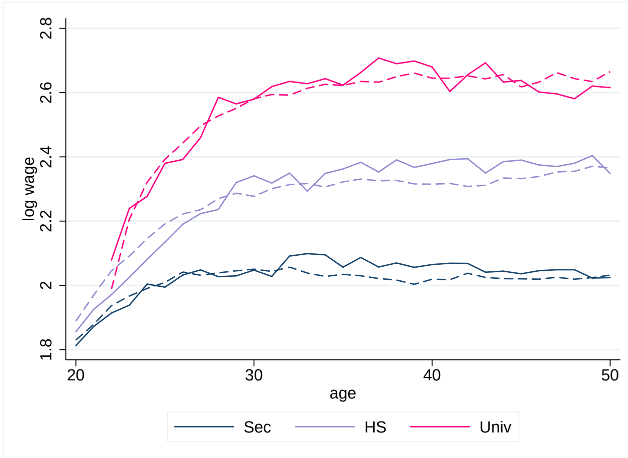

FIGURE 1. WAGES BY EDUCATION AND AGE

Note: Data versus simulated model, in solid and dashed lines respectively.
Source: Blundell, Dias, Meghir and Shaw (2016).

by the mid-30s and for the relative insensitivity of labor supply to short-run wage and tax changes. The results suggest a key role for saving and note implications for labor supply elasticities. As Keane (2016) points out, labor supply responses for the higher educated need to be viewed in a lifetime context where career profiles matter.

Longer-run analysis has to allow for education choices and the results show that education is influenced by tax reform. There is a significant but small effect of increases in tax credit/welfare generosity on education choice, attenuating some of the employment gains. By reducing the utility loss of low wages, tax credits offset some of the financial benefits of education. A key insight is that the insurance value of tax credits for risk averse consumers matters. This is shown to be an important mechanism in driving the results. By reducing the utility loss from the chance of a low wage outcome is significantly reduced.

BDMS also compare the *ex-post* simulated impact of existing reforms that occurred during the data period with impact measures from reduced-form approaches. For example, the ex-post impact of the working families tax credit (WFTC) reform on employment is simulated. This is compared to a matched difference-in-differences estimate for low educated lone parents, using low educated women without children as a comparison group. The two results line up well and are not significantly different. Dynamic models with forward looking behavior invalidate the diff-in-diff assumptions since the comparison group have a non-zero probability of being impacted by the policy at some point in the future and may change their behavior accordingly. But the diff-in-diff parameter remains an interesting moment to check for model misspecification.

The full structural model additionally allows *ex-ante* counterfactual simulations. For example, BDMS study the complete removal of the tax credit system and document important impacts on education choices and life-cycle labor supply. The welfare costs of such reforms highlight the importance of measuring the insurance value of tax-credits.

This illustration shows the power of structural dynamic models to deliver new insights through:

(i) the recovery of 'deep parameters', for example the size of extensive and intensive elasticities in a dynamic model with experience capital, and the differential impact of part-time and full-time work on experience capital.

(ii) the identification of underlying mechanisms such as the separation of incentive from insurance effects of life-cycle decisions; and

(iii) counterfactual simulations such as the ex-ante simulation of a previously unseen reform to the tax and welfare system, namely the complete removal of earned income tax-credits.

There are many other important recent contributions to the structural modeling literature on dynamic life-cycle choices - too many to discuss in detail. Key examples include: Cunha, Heckman and Schennach (2010) which provides important new results on the identification and estimation of the ‘household production’ of cognitive and noncognitive skill formation. French (2005) which shows the key role of retirement incentives separate from preferences in retirement; Meghir, Low and Pistaerri (2015) which separates employment risk from wage risk; Low and Pistaferri (2016) which separates out the dynamic incentives in the disability system; Voena (2015) that shows the potential impact on family formation. All of these papers provide convincing evidence on structural parameters and build our knowledge base on life-cycle decisions.

In all cases they estimate deep parameters, they provide a clear insight into the mechanisms underlying the observed behaviour and they provide policy counterfactuals.

B. *Quasi-Structural Dynamic Models*

We have already seen that in some studies a full counterfactual simulation may not be the objective of interest. A subset of structural paramaters and/or mechanisms may be sufficient. For example, one may estimate ‘life-cycle’ consistent preferences by conditioning on consumption (or saving) which, under intertemporal additive separability, represent a sufficient static for future expectations and discount rates, see Blundell and Walker (1986). Another example is the partial insurance literature, see Blundell, Preston and Pistaferri (2008) in which structural ’insurance’ parameters are recovered consistently without specifying the precise for of expectations. Yet another example is the estimation of an Euler equation for consumption growth which can identify the intertemporal substitution ’Frisch’ elasticity with weak conditions on information and expectations but does not allow a full life-cycle counterfactual analysis of consumption (and labor supply) decisions.

For some aspects of welfare reform, certain ’sufficient statistics’ may be all that is required to characterise an optimal mechanism, partcularly in the case of optimal marginal reform where local derivatives form the sufficient statsitics, see Chetty (2009).

C. *Combining Experimental and Structural Approaches*

An important recent development has been applications which combine structural and experimental evidence. This has produced a number of new insights. For example, Todd and Wolpin (2006) use experimental data to validate a dynamic structural model of child schooling and fertility. Attanasio, Meghir and Santiago (2012) show the usefulness of using experimental data to estimate a structural economic model as well as the importance of a structural model in interpreting experimental results. The availability of the experiment also allow them to estimate the program’s general equilibrium effects, which they then incorporate into the simulations. Karlan and Zinman (2009) use a consumer credit experiment to distinguishing between Adverse Selection and Moral Hazard in the market for consumer credit in South Africa, randomly reducing the interest rate to identify a structural parameter. Duflo, Hanna, and Ryan (2012) use a randomized experiment on the India teachers to identify a structural model to assess whether monitoring and financial incentives can reduce teacher absence and increase learning.

IV. Revealed Preference and Set Identified Structural Models - A Rejoinder

Most structural choice models rest on the use of revealed preference conditions, see McFadden (2005). We have already noted the use of revealed preference conditions in the recent work of Manski (2014) and Blomquist et al (2014).

The structure of decision-making models in delivers certain restrictions that allow the recovery of counterfactuals. For example, the revealed preference conditions of consumer choice theory can be used to place bounds on consumer responses to price and income changes, enabling us to examine the impact counterfactual tax and redistributive policies. Some aspects of decision-making are testable, in the sense that observational data can be used to reject theory. Where it is not rejected it can then be used to generate credible predictions of the impact of counterfactual policies.

As shown by Varian (1982), nonparametric revealed preference theory generates elegant nonparametric tests that can be used to assess whether data on observed consumer choices is consistent with having been generated by utility maximisation. It can also be used to recover information about the utility function and to forecast choices at new budgets or prices. Recent developments have extended these results to models of habits (Crawford, 2010), collective family labor supply (Cherchye et al, 2011) and time inconsitent mdoels (Adams et al, 2014).

Typically revealed preference conditions give rise to inequalities that only set identify counterfactual demands. Nonetheless, recent work has shown how to generate best bounds on counterfactual demands from relative price or tax changes, see Blundell, Browning and Crawford (2008). They also show how adding price information shrinks the identified set and tightens the bounds.

As Bontemps and Magnac (2016) note, most examples of set identified structural models are borrowed from empirical industrial organization. Entry games have been used as a case study and Ciliberto and Tamer (2009) use US data an entry game played by airlines on routes connecting two airports. Several contributions have also been developed in the literature on auctions. One of the first examples is presented by Haile and Tamer (2003). The authors develop a structural model for ascending auctions for which parameters are notoriously difficult to identify because of poor observed information. The authors only exploit rationality constraints on agents behavior. Pakes et al. (2015) develop the estimation of structural models under general rationality constraints.

V. Conclusions

Structural models play a key role in understanding economic behavior and in policy design. They complement reduced form approaches by explicitly incorporating restrictions from economic decision-making models. By doing so they make three related, but distinct, contributions : they estimate deep parameters, they provide a clear insight into the mechanisms underlying the observed behaviour and they provide counterfactuals. In addition, they can be used to reconcile earlier results and consequently help build a knowledge base.

Structural models make explicit the assumptions on preferences and constraints being used to estimate parameters, mechanisms and counterfactuals. But these assumptions need to be tested, assessed and relaxed wherever possible. This has been the theme taken here in this discussion focusing on the structural analysis of labor supply behavior and tax reform. Most reliable analyses in this field have acknowledged the importance of aligning structural models with reduced form evidence and with minimising the reliance on unnecessary assumptions. In turn we have seen that structural models have delivered a series of new insights into behavior and generated useful policy counterfactuals.

As Frisch (1933) noted "No amount of statistical information, however complete and exact, can by itself explain economic phenomena. If we are not to get lost in the overwhelming, bewildering mass of statistical data that are now becoming available, we need the guidance and help of a powerful theoretical framework. Without this no significant interpretation and coordination of our observations will be possible."

References

Adams, Abigail, Laurens Cherchye, Bram De Rock, Ewout Verriest, 2014. Consume Now or Later? Time Inconsistency, Collective Choice, and Revealed Preference, American Economic Review, vol. 104(12), pages 4147-83.

Attanasio. P., Orazio, Costas Meghir Ana Santiago, 2012. Education Choices in Mexico: Using a Structural Model and a Randomized Experiment to Evaluate PROGRESA, Review of Economic Studies, vol. 79(1), pages 37-66.

Peter Arcidiacono, and Robert. A. Miller. 2011, Conditional Choice Probability Estimation of Dynamic Discrete Choice Models With Unobserved Heterogeneity, Econometrica 79 (6), 1823-1867

Aguirregabiria, V and Pedro Mira (2010). Dynamic discrete choice structural models: A Survey, Vol 156, Issue 1, May.

Beffy, Magali., Richard Blundell, Antoine Bozio and Guy Laroque, (2015): Labour supply and taxation with restricted choices, IFS Working Papers , W15/02, revised January 2016

Blundell, R. (2012). Tax Policy Reform: the Role of Empirical Evidence, Journal of European Economics Association, February 10(1):43-77

Blundell, R., A. Bozio, and G. Laroque (2011), Extensive and intensive margins of labour supply: Working hours in the US, UK and France. AER Papers and Proceedings, see also Working Paper 01/11, Institute for Fiscal Studies.

Blundell, R.,M. Browning and I. Crawford, 2008, Best nonparametric bounds on demand responses, Econometrica, 76:1227-1262.

Blundell, Richard, Alan Duncan, Julian McCrae, and Costas Meghir (2000). The Labour Market Impact of the Working Families Tax Credit. Fiscal Studies, 21(1) 75103.

Blundell, R. M. Browning and C. Meghir (1994). Consumer demand and the life-cycle allocation of household expenditures, Review of Economic Studies, vol. 161: 57-80.

Blundell, R., A. Duncan and C. Meghir (1998). Estimating Labor Supply Responses Using Tax Reforms, Econometrica, vol. 66: 827-861.

Blundell, Richard, Joel L. Horowitz, and Matthias Parey, (2012): the price responsiveness of gasoline demand: Economic shape restrictions and nonparametric demand estimation," Quantitative Economics 3 (March), 29-51.

Blundell, R. and H. Hoynes (2004). Has In-Work Benefit Reform Helped the Labour Market?, in R. Blundell, D. Card and R. Freeman (eds), Seeking a Premier League Economy, 411-460, Chicago: University of Chicago Press.

Blundell, R., D. Kristensen, and R. Matzkin, 2014, Bounding Quantile Demand Functions using Revealed Preference Inequalities, Journal of Econometrics, 117:112-127.

Blundell, R. and T. MaCurdy (1999). Labor Supply: A Review of Alternative Approaches, in O. Ashenfelter and D. Card (eds), Handbook of Labour Economics, vol 3: 1559-1695, Amsterdam: Elsevier Science.

Blundell, R., Costa Dias, M., Meghir, C., Shaw, J., 2016. Female labor supply, human capital, and welfare reform. Econometrica 84 (5), 1705-1753.

Blundell, R. and T. MaCurdy (1999), Labor supply: A review of alternative approaches. In Handbook of Labor Economics, Vol. 3 (O. Ashenfelter and D. Card, eds.), 1559-1695, North-Holland, Amsterdam.

Blundell, R. and A. Shephard (2012), Employment, hours of work and the optimal taxation of low-income families. Review of Economic Studies, 79, 481-510.

Blundell, R. and I. Walker (1986). A Life-Cycle Consistent Empirical Model of Family Labour Supply Using Cross-Section Data, The Review of Economic Studies, Vol. 53(4): 539-558, Econometrics Special Issue.

Blomquist, S. and W. Newey (2002), Non-parametric estimation with nonlinear budget sets. Econometrica, 70, 2455-2480.

Blomquist, S. A. Kumar, C-Y Liang and W. Newey (2014) Individual Heterogeneity, Nonlinear Budget Sets, and Taxable Income, mimeo.

Bontemps, Christian and Thierry Magnac (2016) Set Identification, Moment Restrictions and Inference, forthcoming Annual Reviews in Economics.

Card, D. and R. Hyslop (2005). Estimating the Effects of a Time-Limited Earnings Subsidy for Welfare-Leavers, Econometrica, vol. 73(6): 1723-1770.

Cherchye, Laurens, Bram De Rock Frederic Vermeulen, 2011. The Revealed Preference Approach to Collective Consumption Behaviour: Testing and Sharing Rule Recovery," Review of Economic Studies, vol. 78(1), 176-198.

Chesher, A., 2005, Non Parametric Identification under Discrete Variation, Econometrica, 73:1525-1550.

Chetty, R. (2009), Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods, Annual Review of Economics Vol. 1: 451-488.

Ciliberto, F., and E. Tamer, 2009, "Market Structure and Multiple Equilibria in Airline Markets", Econometrica, 77:1791-1828.

Crawford, Ian. 2010. Habits Revealed, Review of Economic Studies, vol. 77(4), 1382-1402.

Cunha., Flavio, James J. Heckman and Susanne M. Schennach, 2010. Estimating the Technology of Cognitive and Noncognitive Skill Formation, Econometrica, vol. 78(3), 883-931.
Duflo, Esther., Rema Hanna, and Stephen P. Ryan (2012) Incentives Work: Getting Teachers to Come to School. American Economic Review 2012, 102(4): 1241-1278.

Fan, X., Seshadri, M., and C. Taber, (2015). Estimation of a Life-Cycle Model with Human Capital, Labor Supply and Retirement, Working Paper, University of Wisconsin, April.

Fang, H. and Y. Wang (2015): Dynamic Discrete Choice Models with Hyperbolic Discounting, with an Application to Mammography Decisions, International Economic Review, 56, 565-596.

French, E. (2005). The Effects of Health, Wealth, and Wages on Labour Supply and Retirement Behaviour, The Review of Economic Studies, vol. 72(2): 395-427.

Hausman, Jerry A. and Whitney K. Newey, (1995): Estimation of Exact Consumers Surplus and Deadweight Loss," Econometrica 63 (November), 1445-1476.

—, (2013): Heterogeneity and Average Welfare, cemmap working paper CWP34/13 (July).

—, (2015): Welfare Analysis, forthcoming, Annual Reviews.

Haile, P., and E.Tamer, 2003, Inference with an Incomplete Model of English Auctions, Journal of Political Economy, 2003, 111:1-51.

Heckman, J. J. and T. E. MaCurdy (1980). A Life Cycle Model of Female Labour Supply The Review of Economic Studies, vol. 47(1): 47-74.

Heckman James J. (1991) Identifying the Hand of Past: Distinguishing State Dependence from Heterogeneity', American Economic Review, Vol. 81(2), May, 75-79.

James James J. John E Humphries and Gregory Veramendi (2016). Dynamic Treatment Effects', Journal of Econometrics 191, 276-292.

Heckman, James J. and S. Navarro (2007) Dynamic discrete choice and dynamic treatment effects' Journal of Econometrics, 136, 341-396.

Heckman, J.J., and Rong Hai (2016). Inequality in Human Capital and Endogenous Credit Constraints, Working paper, University of Chicago.

Hausman, J. (1985), The Econometrics of Nonlinear Budget Sets, Econometrica 53 : 1255 1282.

Ho, K,. and A. Rosen, 2015, Partial Identification in applied Research: Benefits and Challenges, CEMMAP Working paper 64/15.

Hotz, J., and R.Miller, Conditional Choice Probabilities and Estimation of Dynamic Models, Review of Economic Studies 60 (1993), 497-529

Imai, S., Keane, M.P., 2004. Intertemporal labor supply and human capital accumulation. International Economic Review 45, 601-641.

Karlan, D. and Zinman, J. (2009), Observing Unobservables: Identifying Information Asymmetries With a Consumer Credit Field Experiment. Econometrica, 77: 19932008.

Keane, M.P., Moffitt, R., 1998. A structural model of multiple welfare program participation and labor supply. International Economic Review 39, 553-590.

Keane M. P. and K. I. Wolpin (1997). The Career Decisions of Young Men, Journal of Political Economy, vol. 105(3): 473-522.

Keane, M.P. (2010): Structural vs. atheoretic approaches to econometrics, Journal of Econometrics, 156, 3-20

Keane, M. (2011), Labor supply and taxes: A survey. Journal of Economic Literature, 49, 961-1075.

McFadden, D. (2005) Revealed Stochastic Preference: A Synthesis, Economic Theory 26, 245-264.

Matzkin, R.L., 1994. Restrictions of economic theory in nonparametric methods. In: Engle, R., McFadden, D. (Eds.), Handbook of Econometrics, vol. 4. North- Holland, New York, pp. 2523-2558.

Matzkin, R.L. (2008) Identification in Nonparametric Simultaneous Equations, Econometrica, Vol. 76, No. 5, 945978.

Magnac, T. and D. Thesmar (2002): Dynamic Discrete Choice Processes, Econometrica, 70, 801816.

Manski, C.F. (2014), Identification of incomeleisure preferences and evaluation of income tax policy, Quantitative Economics 5, 145-174.

Mirrlees, James, Stuart Adam, Tim Besley, Richard Blundell, Steve Bond, Robert Chote, Malcolm Gammie, Paul Johnson, Gareth Myles, and James Poterba (eds) (2011). Tax by Design: The Mirrlees Review. Oxford University Press for Institute for Fiscal Studies.

Moffitt, R., (1990). The Econometrics of Kinked Budget Constraints, Journal of Economic Perspectives, vol. 4(2), pages 119-139.

Moffitt, Robert (2016). Economics of Means-Tested Transfer Programs in the United States, Volumes I & II.. NBER, University of Chicago Press.

Norets, A., and X. Tang, Semiparametric Inference in Dynamic Binary Choice Process, Review of Economic Studies 81 (2014), 122962.

Olley, G.S. and Pakes, A. (1996) The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica, 64(6), 1263-97.

Pakes, A., J. Porter, K. Ho and J. Ishii, 2015, Moment Inequalities and their Applications, Econometrica, 83(1), 315-334.

de Paula, A., 2016, Econometrics of Network Models, CeMMAP Working Paper 06/16.

Postel-Vinay, F., Robin, J.-M., 2002. Equilibrium wage dispersion and with heterogeneous workers and firms. Econometrica 70, 22952350.

Rust, J. (1994): Estimation of dynamic structural models, problems and prospects: discrete decision processes, in C. Sims (ed.) Advances in Econometrics. Sixth World Congress, Cambridge University Press.

Rust, J. (2010): Comments on: “Structural vs. atheoretic approaches to econometrics” by Michael Keane, Journal of Econometrics, 156, 21-24.

Todd, P. and K. Wolpin (2006): Using Experimental Data to Validate a Dynamic Behavioral Model of Child Schooling and Fertility American Economic Review, 96(5): 1384-1417

Hal Varian (1982), ”The Nonparametric Approach to Demand Analysis”, Econometrica, 50(4), 945-973.