

Evolution of trade theories and technological change endogeneity in macroeconomic models

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Since the early years of large-scale economic model development, representation of international trade has been dominated by the Armington assumption of differentiated commodities by country of origin, within a constant returns-to-scale perfect competition framework (Armington, 1969). The Armington trade structure first appeared in CGE modelling through the ORANI model (Dixon et al., 1977), and its tractability advantages explain its wide adoption by such macroeconomic models. Its simplicity, however, also constitutes its main limitation: it does not allow representing and quantifying firm-level or productivity effects. This is also why, alongside improving computational capacities, there have been ever-growing discussions among the economic modelling community on shifting from the traditional Armington assumption to more modern theories that are more consistent with micro-level observations. In this direction, the Krugman (1980) and Melitz (2003) models have constituted modern trade schemes reflecting firm-level differentiation. However, their integration into large-scale quantitative systems models representing a large number of commodities still entails considerable computational and empirical data challenges. Despite computational barriers, the Krugman and Melitz models have remained at the centre of debate, especially among those attempting to go beyond the Armington assumption in computational economics, and particularly in CGE modelling. Beyond these three, there also exist other trade mechanisms that have gained traction recently, such as the Eaton-Kortum (Eaton & Kortum, 2002) and Bilateral Representative Firm (BRF) models (Balistreri et al., 2025).

At the same time, early macroeconomic models typically relied on exogenous technological change (TC)—e.g., represented through the ‘autonomous energy efficiency improvement’ (AEEI) parameter (Duan et al., 2017). With the rise of endogenous growth theory, modelling has moved toward the endogenisation of technological change, with technological progress increasingly calculated endogenously in the models as a result of economic activity, such as R&D investment, economies of scale, and learning-by-doing processes, rather than an exogenously determined trend. The modern endogenous growth literature draws heavily on the work of Romer (1990) and places knowledge, as a distinct form of capital accumulated through R&D activities, at the centre of the growth process. A branch of technological change endogenisation uses learning curves to represent technical progress through cost reductions, depending on cumulative production (or

capacity) levels, while another established approach emphasises the concept of knowledge spillovers, by representing the diffusion of production experience across sectors and/or countries (Gersbach & Schmutzler, 2003). Developments in growth theory have “driven” the incorporation of TC in macroeconomic models, especially in CGE models, in which technology is typically represented through nested sectoral production functions. Introducing endogenous technological change (ETC) into such models entails the specification of a mechanism that links economic variables (e.g., output/production, R&D expenditure, trade flows, etc.) to production functions’ parameters that represent some type of efficiency and makes sense to be improved.

We carry out two systematic literature reviews, across titles, abstracts, and keywords in Scopus, one on each subject (trade theory¹, endogenous technological learning²), to capture the state of the art while assess how economic modelling has advanced in time.

From the synthesis of the reviewed papers (to be presented at the conference), some useful conclusions can be summarised.

When it comes to trade theories, a core weakness of the Armington model is that it cannot capture selection effects, since the trade diversion comes only through the Armington elasticities, while changes in trade flows are conditioned by pre-existing shares; therefore, Armington models can only capture adjustments coming from changes in export volumes, which is not aligned with empirical studies highlighting the contribution of new varieties in export markets (Akgul et al., 2016). Krugman is a completely demand-side variety-driven model, while Melitz considers not only demand-side variety effects in a multi-commodity setting but also supply-side productivity effects. The Krugman model may not necessarily be fit-for-purpose within a multi-region framework—for instance, once a commodity is produced, it goes to every region, meaning that symmetric varieties enter the market at the level of region and, once a variety is offered to one market, it is offered to all markets; therefore, only when trade costs “approach infinity” will some consumers around the globe not consume that commodity (Balistreri et al., 2025). The Melitz approach is especially important for the analysis of free trade agreements, where the impacts depend largely on changes in non-tariff measures (NTMs), which affect largely the trade costs; in particular, the differentiation between fixed and variable costs in bilateral trade that is embodied in Melitz-driven CGE models allows for more realistic assessments of NTMs (Fugazza & Maur, 2008). Another feature of the Melitz scheme is that trade may induce changes in productivity, even though the production technology of a country is the same; aggregate productivity changes are brought by the composition of the firms within a sector, as opposed to the allocative efficiency effects in traditional models with homogeneous firms and the Armington assumption.

From a technical change perspective, the majority of modern large-scale models adopt ETC mechanisms that are grounded on learning-by-doing or knowledge stock accumulation through R&D, reflecting the foundations of Arrow (1962) learning model and Romer (1990) capital formulation, respectively. Learning-based mechanisms remain attractive due to their intuitive interpretation: production becomes more efficient as it increases. R&D-based knowledge mechanisms are also quite popular since they explicitly model innovation efforts (private and

¹ ("computable general equilibrium" OR "CGE model" OR "macroeconomic model") AND ("Krugman" OR "Melitz" OR "firm heterogeneity" OR "product differentiation")

² ("computable general equilibrium" OR "CGE" OR "macroeconomic model") AND ("technical change" OR "technological progress" OR "technical progress" OR "endogenous innovation" OR "knowledge transfer" OR "knowledge flow" OR "learning by doing" OR "learning by researching" OR "endogenous productivity" OR "endogenous growth" OR "technological spillover" OR "knowledge spillover" OR "learning by exporting" OR "firm heterogeneity")

public). We also highlight the growing importance of spillover mechanisms (across sectors and/or regions): spillovers are often transmitted through trade, FDI, or the introduction of new varieties within Dixit–Stiglitz structures, while approaches such as Parrado & De Cian (2014), Tarr (2013), and Robinson et al. (2002) demonstrate that international trade can serve as a key driver for embodied technology transfer, making the intersection of trade and technology a central element of ETC modelling. Directed technical change-enabled models allow innovation to be endogenously targeted toward specific factors (e.g., labour of different skill levels, energy vs. capital); these frameworks capture feedback loops between policy (e.g., carbon pricing, trade liberalisation), factor prices, and the direction of innovation—something that neither simple learning mechanisms nor pure R&D accumulation models can represent. Finally, price-induced input augmentation and backstop technology approaches are rarely used as primary ETC mechanisms in CGE models and are characterised as semi-endogenous mechanisms; they remain conceptually important but more often employed in bottom-up rather than CGE models.

We also note key challenges across both branches of literature and scientific advances.

While the Melitz specification is theoretically appealing, its existing implementations in CGE models seem to struggle with numerical stability, implying limitations in sectoral and regional detail. The endogenisation of free entry and exit in a multi-sector, multi-region Melitz model that includes intermediate inputs may give rise to computational difficulties related to multiple and/or corner equilibria. Faced with the inherent computational challenges, modellers have invented various solutions to overcome associated barriers and adopt—at least partially, not globally across their models—a Melitz-based mechanism; for instance, Bekkers & Francois (2018) use a set of endogenous supply and demand shifters, such that an Armington model “mimics” a Melitz one, an approach sharing similarities with the decomposition algorithm of Balistreri & Rutherford (2013), where the Armington demand system is iteratively re-calibrated (in the latter case, the model involves nine sectors in total, with only two being of Melitz type). Due to the assumption that import prices are identical for each source country, incorporating the Eaton-Kortum framework in a GTAP model is quite complicated and the code must be restructured regarding the price basis of the model. A complete implementation covering all (65 in v.11) sectors of the GTAP Data Base seems to be numerically challenging: firm heterogeneity requires additional information that is not readily available in the standard database, such as on key firm heterogeneity parameters, fixed set-up costs, and fixed trading costs.

The integration of endogenous technological change faces various challenges. Conceptually, CGE models, by construction, rely on a well-structured behaviour of agents (e.g., nested CES structure for producers), while innovation processes, potentially characterised by increasing returns, heterogeneity in agents, etc., are difficult to be aligned with the structure and granularity level of established models; for instance, increasing returns to knowledge might conflict with the constant return assumptions of standard CGE production. Empirically, in R&D-based mechanisms, knowledge stocks depend heavily on assumptions on initial stocks and depreciation, sector-specific R&D expenditures are poorly documented for various countries, while in learning-based mechanisms—when historical data are sparse—the determination of learning rates entails uncertainties that should be considered by modellers. Computationally, ETC dynamic mechanisms increase models’ “non-linearity” in various ways, which might lead to non-convexities and the presence of multiple equilibria. From a policy interpretation viewpoint, TC endogenisation introduces new layers of feedback between policy (exogenous) variables and model outputs (e.g., modellers should account for potential double counting of technological improvements when learning-by-doing and R&D effects are considered simultaneously in the

mechanism), while the trade-technology interaction might be modelled in a quite simplified way (e.g., ignoring domestic spillovers).

Keywords: trade theories; Armington; Melitz; Krugman; technical change; learning-by-doing; endogenisation; CGE modelling; macroeconomic models

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