Paper Title: Technology Adoption and the Timing of Environmental Policy: Evidence from Efficient Lighting

1 Summary

The over-arching question this paper attempts to address is about timing of support for technologies that have varying levels of externalities: how does early support for somewhat clean technologies effect later diffusion of cleaner technologies? Specifically, how do early efficiency standards and subsidies for moderate-efficiency lightbulbs and affect later adoption of high-efficiency lightbulbs (LEDs).

To address these question, the author uses a discrete choice framework to estimate structural parameters of demand for three types of lighting, where the third type enters the market late. By modifying a static-utility BLP-style nested loop, the author offers a novel approach to endogenously solve for changes in consumers' return-to-market and consumer heterogeneity. Using the estimated demand parameters, the author analyzes the welfare trade-offs between different counterfactual scenarios of (1) a delayed efficiency standard; and (2) a different phase-out schedule of subsidies on the moderate efficiency technology.

The author finds that both early subsidies and efficiency standards of the moderately efficient technology has welfare losses associated with decreased adoption of the later more efficient technology, but that those losses are somewhat offset by the welfare gains of reducing externalities from early adoption of the moderately efficient technology; in the case of efficiency standards, the losses were more than offset by gains from early reduced externalities. To address the neglected supply-side model, the author estimates the new path that the price of the more efficient technology would need to take in order to have the same final market share – this is an alternative innovation path. Ultimately, the take-home story is that both early efficiency standards and subsidies on less-efficient technology to increase early adoption can be a welfare-improving policy.

2 Critique

The dirty-clean-cleaner model of differentiated goods and delayed market entry under static consumer demand is an edition to the existing modeling frameworks utilizing the BLP estimation technique. As an ex-post policy evaluation tool, this seems like a useful framework for examining the effects of early policies on more effective technologies that will come down the road. However, the simplicity of the analysis relies on understanding the ex-post path of innovation, or being able to forecast it with some accuracy. This seems of use mostly in backward-looking analyses, since it would be unlikely in most realistic policy scenarios to understand ahead of time when future technology is going to be developed (especially if the timing introduction of the technology to the market is completely exogenous to the policy intervention, as it is in this model).

Overall, I am uncertain of the usefulness of a framework like this. The author admits that the results are highly specific to this context and heavily depend on characteristics of the technology. So the results do not have external validity. The question is then: what is the use of the model? There is probably inherent value in understanding the ex-post effects of policy on more advanced technology diffusion. The goal I would have, though, is to use those results to generalize to future policy. This type of mysterious future technology that appears in the middle of the modeled study period seems like a very narrow use case because it requires understanding with some certainty the arrival and costs of a technology, years in advance. An unlikely scenario.

However, I appreciate the modification of the BLP nested loop as an example of endogenizing consumer's coming-to-market when their past choices affect the time between purchases. I can see this being useful in other contexts regarding product quality.

Due to limitations of the data, some assumptions were needed to estimate the model that make it less credible as a legitimate empirical result. This paper seems to be in a no-mans-land of having less-than-credible results and a particularly narrow methodological contribution. Footnotes throughout indicate that a future iteration may provide more robust empirical results.

3 Key Issues to address

3.1 Supply Side

The author recognizes this short cumming, so I will be brief: to understand the effects on the future market share and success of technology A of a subsidy on technology B, we need to understand impacts on investment and innovation of technology A. Across counterfactuals, this model assumes an initial market share identical to the observed initial market share – assuming the initial and following market shares are exogenous to the policy. In reality, early investment in LEDs may have been substantially different if subsidies for CFL bulbs were phased out later or if the efficiency standards came in later; e.g., perhaps the early efficiency standards showed investors there could be short-term returns on investing in LEDs and investment for LEDs would be delayed by delaying efficiency standards, thus decreasing the rate of price declines for LEDs. More investment could have also changed the rate of learning-by-doing, but without modeling the supply of LEDs specifically, it is hard to know.

Lee (2013) (a cited article) combines consumer demand with a model of supplier hardware adoption. This could be a useful framework because, I believe, many of the early popular brands of LED lightbulbs were name-brands. So the supply side could also be modeled as name brands adopting new LEW technology to sell to consumers.

3.2 Other Rebates / subsidies

The author discusses several types of subsides for CLF lightbulbs, mainly buy-down programs where the sticker price is the subsidized price that shows up in the data, and rebate programs where consumers use coupons to get a lower price and the original sticker price shows up in the data. So, the rebate subsidies are unrecoverable given the dataset. If there are other unaccounted-for subsidies for CFL lights, some customers face a smaller price than that shown in the data, and the demand elasticities may be incorrectly estimated. For example, if consumers face at most one type of subsidy, and some consumers face a rebated price lower than that in the data, then the consumers on the lower part of the demand curve probably have more of the buy-down priced consumers, and the consumers on the higher-price portion of the demand curve are actually facing lower prices than the data tell us. Then the demand curve is tilted down, resulting in a more elastic demand for CFLs. This is an issue for the counterfactual welfare analyses – for example, consider the counterfactual that CFL subsidies were phased out sooner: there may not be as many consumers willing to pay high prices for more efficient lighting as thought, so there would be fewer consumers purchasing LEDs after the earlier phase out, meaning an earlier phase out may have smaller welfare gains (from reduced externalities) than estimated.

If these other rebates are also part of this national CFL subsidy being analyzed, without accounting for these other rebates, the conclusions of the counterfactual analysis may be incorrect. However, on page 41, the author mentions EPA data on counties that have lighting rebate programs and I wonder if that data includes the amount of the CFL subsidy? If it does not, perhaps the author could include an indicator for CFL subsidy/rebate in the market to analyze these counties separately, or add an exogenous subsidy parameter to the utility function for ”average subsidy” in these counties with rebates. This would be a way to model a consumer that faces some subsidy from the price they pay in the data. Then the analysis could be run with different values of the average subsidy to see if the conclusions are sensitive to the amount of the average subsidy assumed to be occurring in these counties with rebate programs.

4 Minor Suggestions

(4.1) Pg. 32: The identifying initial condition assumption that CFL, halogen, and incandescent bulbs shares are uniform across demographic groups seems very unlikely. It may not affect the conclusions very much, but I have no way of knowing that. Since these initial conditions are necessary for estimating the entire model, it seems critical for credibility of the results that you show the results are not contingent upon this uniformity assumption. I would like to how much the results change if this uniformity condition does not hold – e.g., if the share of incandescent bulbs is higher in lower income / low climate change belief groups and CFLs are higher in higher income / high climate change belief groups. I'm not listing this as a major point because, as the paper stands with the updated BLP algorithm, it makes a nice methodical contribution that does not hinge on this initial data-limitation assumption – methodology that other applied economists can still follow in applications where they may have data that gives them the correct initial shares.

(4.2) Pg. 51: Hendel, Nevo 2006 is in the bibliography twice.