31E99906 Microeconomic policy

Lecture 9: Predicting and valuing impacts

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Government initiated a national test run for universal basic income – why?

Report of the ministry of the social affairs and health 2019:9

Plan for the lecture

Objective

In practise, analysts are often expected give recommendations based on numbers. What the conceivable approaches to producing the numbers, given the time and other constraints? In this lecture, we proceed from ideal to practical approaches.

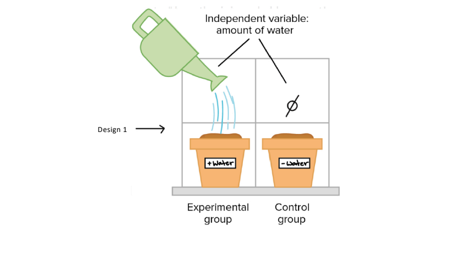
- Consumer welfare changes $\rightarrow$ How to implement the concepts from the first week lectures in practise?
- Regulation $\rightarrow$ The optimal regulated prices: one needs to estimate demand and consumer surplus from the activity
- IPR $\rightarrow$ The debate on patents is about the consumer gains to be evaluated
- Mergers $\rightarrow$ We already saw multiple methods for evaluating the impact

Three Questions

1. What are, in principle, the designs that can be used for evaluating impacts? First part of the lecture: general classification of designs
2. What are the main sources information for analysts to be used in predicting impacts of the policy at hand? Second part: Context specific cases illustrating the general classification
3. Analysts often have to measure impacts that are not directly observed in the market data. What are the approaches for measuring? Third part: indirect valuation approaches

1. Alternative Experimental Designs

- Design 1: Classical Experimental Design
  - The treatment and control groups are measured both before and after the treatment. The design uses random assignment to assign individuals to the groups, which leads to high internal validity. Thus, this is the best of the five alternative designs. However, it is sometimes impractical or infeasible. Like all evaluation designs, it may not provide external validity – that is, it may not be possible to generalize the findings to other groups or time periods.



- Design 2: Classical Experiment without Baseline Data
  - This is the same as Design 1, but no baseline data are collected. As a result, there is a problem in knowing how similar the two groups actually are. This may result in less internal validity
  - Collection of pretreatment information date may influence behavior so sometimes Design 2 may be preferred over Design 1

Randomization in action

Integration SIB project

For immigrants to find employment as quickly as possible is important in many respects. It facilitates their integration to the Finnish society, eases the shortage of labour faced by Finnish employers, and leads to public savings by increasing tax revenue. The Integration SIB project aims to find employment to 2,500 immigrants within the next three years.

In the experiment, implemented by the Ministry of Economic Affairs and Employment, the employment of immigrants is promoted through private investment, using the SIB (Social Impact Bond) model of impact investing. Funds for the activity are collected from investors who also bear the economic risk. The State only pays for the outcome, which in this case means savings in the public sector.

The Integration SIB project boosts the employment of immigrants by bringing together companies and employees and by customising the training of immigrants according to what is needed at workplaces.

The companies participating in the experiment represent sectors that have difficulties in finding workforce, such as the manufacturing industry, building, trade and services. Jobs in academic sectors may also be found via SIB. The experiment is first carried out in Uusimaa and Southwest Finland and it will be extended to regions where there is a shortage of labour as considered necessary.

- Design 3: Before and After Comparison
    - There is no control group. The advantage of this design is that it is easy and inexpensive to implement. The disadvantage is the design's low internal validity. This type of design is only good when a control group is not available and if non-program factors are unlikely to affect outcomes of interest.
- Design 4: Non-Experimental Comparison without Baseline
    - This is similar to Design 2 but without random assignment. Because the control group is not selected on the basis of random assignment, it is sometimes called a quasi-control group design. The lack of baseline data means there is no way of controlling for differences between the groups, which can lead to sample selection bias (systematic difference between the groups that cannot be taken into account).

- Design 5: Non-Experimental Comparison with Baseline
    - This includes baseline data, which increases internal validity because one can control and adjust the data for measured differences between the treatment and control groups. There is still a problem when the groups differ from one another in terms of unmeasured characteristics (e.g., motivation).

2. The main sources of information for predicting policy impacts and valuing them

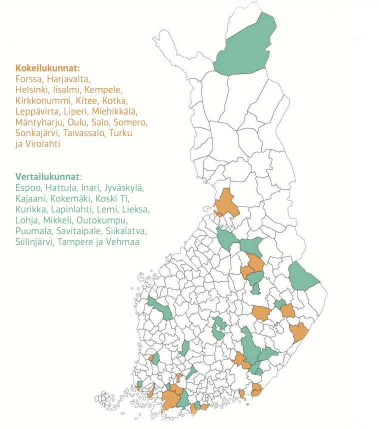
1. Predictions Using Data from an On-Going Policy

- Sometimes the relevant policy questions are whether a policy in place should be continued, terminated, or replicated. Inferences about impacts of the on-going policy can serve as the basis for predicting impacts to inform answers to the policy questions
- When data on a policy are available, we "look back" (make inferences) to "look forward" (make predictions).
- How to make inferences? Ideally: the policy is designed to produce information, experimental or quasi-experimental designs (In fact, the government has a strategy to move towards evidence-based policy making)

Illustration 1: An experiment on providing five-year-olds with free of charge early childhood education and care (ECEC)

An experiment on providing five-year-olds with free of charge early childhood education and care (ECEC) was launched by the Government for the period 2018–2020. The purpose of the experiment was to increase the participation of five-year-olds and their siblings in ECEC and to promote their guardians' employment. The experiment also aimed to develop the pedagogy and service counselling of ECEC. The long-term goals were strengthening educational equality in Finland as well as increasing participation rate in early childhood education and care, which currently is lower than in the other Nordic countries.

Municipalities in the ECEC experiment and the control group



Where does this design fit in the general listing of experimental designs?

Illustration 2: Cost and benefits from a payroll tax cut. Very recent policy debate.

- Korkeamaki and Uustitalo: "Employment and wage effects of a payroll-tax cut: evidence from a regional experiment", Int Tax Public Finance (2009) 16: 753-772

  "[...]we evaluate the effects of a regional experiment that reduced payroll taxes by 3-6 percentage points for 3 years in northern Finland. We match each firm in the target region with a similar firm in a comparison region and estimate the effect of the payroll tax reduction by comparing employment and wage changes within the matched pairs before and after the start of the experiment. [...], the reduction in the payroll taxes led to an increase in wages in the target region. The point estimates indicate that the increase in wages offset roughly half of the impact of the payroll tax cut on the labor costs. The remaining labor cost reduction had no significant effects on employment."

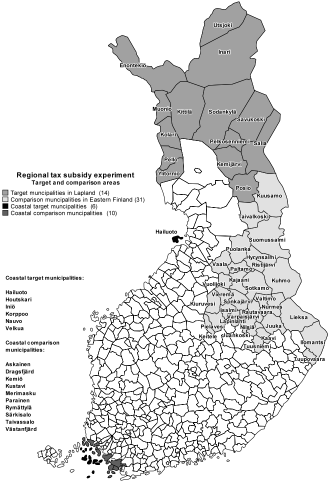
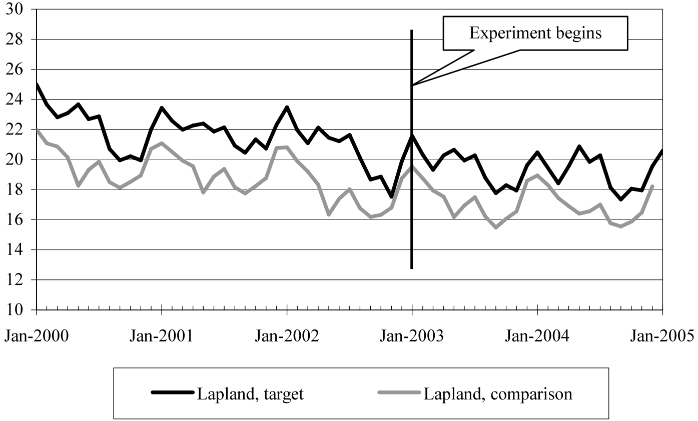


Fig. 1 Target and comparison regions in the Finnish pay-roll tax cut experiment

source: Korkeamaki and Uusitalo



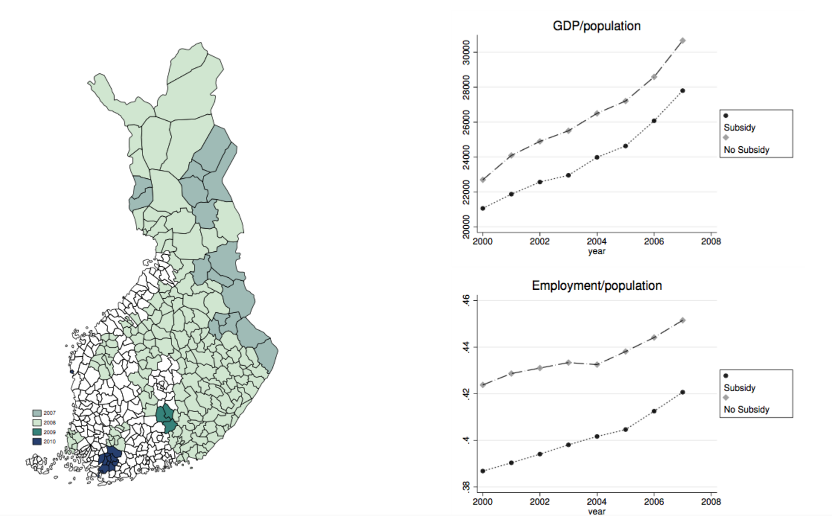
Employment weighted average of the municipality level unemployment rates reported by the Ministry of Labour. These unemployment rates are calculated by dividing the number of unemployed job seekers in the unemployment register by the number of people in the labor force calculated from administrative data in the end of year t–2.

Illustration 3: Effects of subsidizing the first employee in the firm.
Regional subsidy in Finland in 2007-2011: Is the policy effective?

- Annika Nivala, doctoral thesis work
- 30% of wage costs of the first employee in the first and 15% in the second year

Question: How to design an experiment to learn about impacts? If you are interested in writing a case study on this, contact *here*

Illustration 3:Subsidized areas



source: Annika Nivala

2. Predictions Based on Single Evaluation of a Similar Policy

Illustration 1: the costs and benefits of a maternity leave program. What are the gains from extending the maternity leave period?

- Carneiro, P. et al. (2015, JPE):

  "We study a change in maternity leave entitlements in Norway. Mothers giving birth before July 1, 1977, were eligible for 12 weeks of unpaid leave, while those giving birth after that date were entitled to 4 months of paid leave and 12 months of unpaid leave. The increased time spent with the child led to a 2 percentage point decline in high school drop- out rates and a 5 percent increase in wages at age 30. These effects were larger for the children of mothers who, in the absence of the reform, would have taken very low levels of unpaid leave."

Variable	Difference (1)	Differences (2)
Children:		
High school dropout	−.020*	−.032**
	(.011)	(.013)
College attendance	.017	.036**
	(.014)	(.016)
Log earnings at age 30	.045**	.072***
	(.022)	(.026)
Mothers:		
Prereform characteristics:		
Years of education	−.023	−.009
	(.063)	(.071)
Log income 2 years prior to the birth of the child	−.014	.003
	(.031)	(.029)
Outcomes:		
Average log income +/−1 year around year of birth	.037	.008
	(.027)	(.031)
Employed 5 years after the birth of the child	−.002	−.007
	(.012)	(.014)
Log income 5 years after the birth of the child	−.018	−.080
	(.138)	(.157)

Note.—Column 1 shows the coefficients of a regression of each of the variables on an indicator for being born in July 1977. The sample included only individuals born in June and July of 1977. For col. 2, we added to the sample those born in June and July of 1975, 1978, and 1979, and we regressed each of the variables on a year indicator, a month of birth indicator, and the interaction of the two. We report the coefficient on the latter.

* Significant at 10 percent.

** Significant at 5 percent.

*** Significant at 1 percent.

Where does this design fit in the general listing of experimental designs?

Illustration 2: Do Consumers Respond to Marginal or Average Price?, Koichiro Ito, AER 2015

> *Nonlinear pricing and taxation complicate economic decisions by creating multiple marginal prices for the same good. This paper provides a framework to uncover consumers' perceived price of nonlinear price schedules. I exploit price variation at spatial discontinuities in electricity service areas, where households in the same city experience substantially different nonlinear pricing. [...] strong evidence that consumers respond to average price rather than marginal or expected marginal price. This suboptimizing behavior makes nonlinear pricing unsuccessful in achieving its policy goal of energy conservation and critically changes the welfare implications of nonlinear pricing.*

Illustration 2: Marginal and average prices

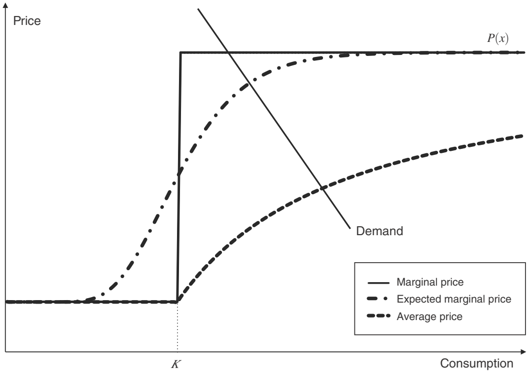


Illustration 2: Discontinuites

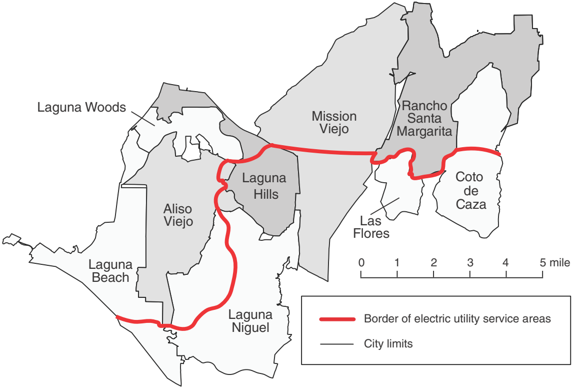


Figure 2. Border of Electricity Service Areas in Orange County, California

Illustration 2: Results

TABLE 2—ENCOMPASSING TESTS: MARGINAL PRICE VERSUS AVERAGE PRICE

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(\textit{marginal price}_t)$	−0.034		0.002			
	(0.004)		(0.011)			
$\Delta \ln(\textit{average price}_t)$		−0.051	−0.054			
		(0.005)	(0.015)			
$\Delta \ln(\textit{marginal price}_{t-1})$				−0.050		0.006
				(0.004)		(0.011)
$\Delta \ln(\textit{average price}_{t-1})$					−0.074	−0.082
					(0.005)	(0.015)

Notes: This table shows the results of the IV regression in equation (3) with fixed effects and control variables specified in the equation. The unit of observation is household-level monthly electricity usage. The dependent variable is the log change in electricity consumption in billing period t from billing period $t - 12$. The sample period is from January 1999 to December 2007 and the sample size is 3,752,378. Standard errors in parentheses are clustered at the household level to adjust for serial correlation.

Illustration 3: measurement of pollution externalities Chen et al. (2013, PNAS) consider a quasi-experimental empirical approach is based on China's Huai River policy, which provided free winter heating via the provision of coal for boilers in cities north of the Huai River but denied heat to the south. An arbitrary Chinese policy that greatly increases total suspended particulates (TSPs) air pollution is causing the 500 million residents of Northern China to lose more than 2.5 billion life years of life expectancy.

Illustration 3: China's Huai River policy

Figure 2: The cities shown are the locations of the Disease Surveillance Points. Cities north of the solid line were covered by the home heating policy.

Illustration 3: Crossing the river, impact on pollution

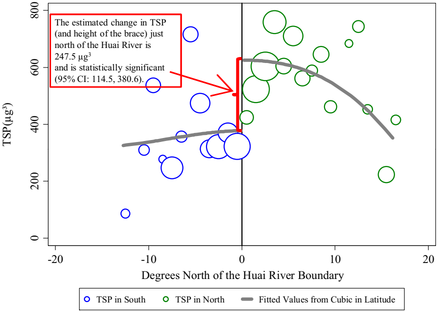


Fig. 2. Each observation (circle) is generated by averaging TSPs across the Disease Surveillance Point locations within a 1° latitude range, weighted by the population at each location. The size of the circle is in proportion to the total population at DSP locations within the 1° latitude range. The plotted line reports the fitted values from a regression of TSPs on a cubic polynomial in latitude using the sample of DSP locations, weighted by the population at each location.

Illustration 3: Crossing the river, impact on mortality

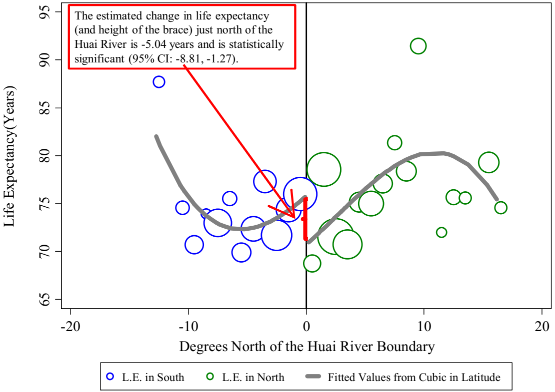


Fig. 3. The plotted line reports the fitted values from a regression of life expectancy on a cubic in latitude using the sample of DSP locations, weighted by the population at each location.

Can we apply these lessons as such?

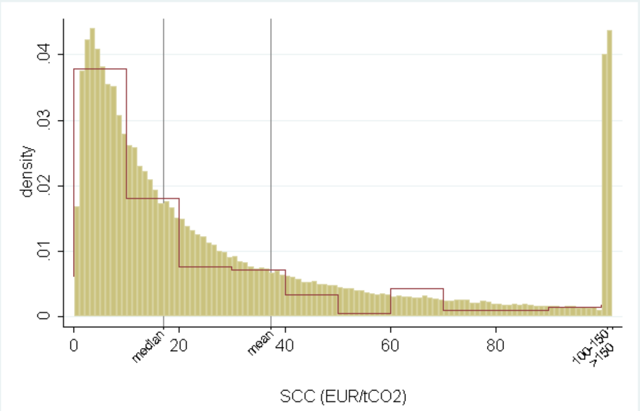
- Does the policy have the same underlying model?
- How closely do the details of the policies conform?
- What is the quality of the evaluation of the similar policy? Is it based on an experiment? If not, does the quasi-experimental design provide a good basis for inference?

3. Predictions Based on Meta-Analyses of Similar Policies

Meta-analysis seeks to use the information in the studies to find an effect size and its variation. They typically have the following elements:

- Identification of relevant evaluations. Social scientists often limit their reviews to published evaluations: publishing bias!
- Application of a standardized measure of size effect to facilitated comparisons across studies. For example, a meta-analysis of educational interventions might convert the gains in different achievement tests to changes in standard deviations.
- Computation of an overall effect and its standard deviation.

Illustration: "The social cost of carbon estimates", Richard Tol, Journal of Economic Perspectives, 2009. But see also critical assessment, *(Link)*



source: Tol, 2009

4. Predictions using generic elasticities

Absent relevant evaluations of the policy itself, it may be possible to predict impacts using elasticities. Search the general economics literature (e.g. ECONLIT, Google Scholar, JSTOR). The policy may effectively change the price of a good seen by some target population. A price elasticity of demand for the good could then be used to predict a change in the quantity of the good consumed. Search for meta-analyses of important elasticities:

- Gasoline: Goodwin, P., Dargay, J., Hanly, M., 2004. Elasticities of road traffic and fuel consumption with respect to price and income: a review. Transport Reviews. 24 (3), 275-292.
- Residential water use: de Groot and Nijkamp, Land Economics, 2003
- electricity: M. Espey, Energy Economics, 2004
- cigarettes: Gallet C and List J. Cigarette demand: a meta-analysis of elasticities. Health Economics 2003

Illustration 1: Suppose HSY (Helsinki water utility) considers raising the price of water usage to reduce the average usage per person. Currently, the average per person in helsinki is 158 litres/day, and the target is 130. The current price is 1.25 e/m^3. You have a limited time budget for finding an estimate for the price increase needed, and for calculating the consumer loss (surplus loss) from the policy.

- find a survey of elasticities: you'll find a number close to $-.5$
- pick a functional form for demand: $q = \alpha_0 - \alpha_1 p$
- use the Helsinki consumption-price observation for finding α_0, α_1. But you need one more observation: look at the Tampere or Turku data.
- use the calibrated curve to obtain the number and the change in the consumer surplus.

Illustration 2: Finnish state-owned Baltic Connector Oy and Estonian state-owned Elering AS has made the decision to build the Balticconnector gas pipeline between Finland and Estonia by the end of 2019. The project is part of the Baltic Energy Market Interconnection Plan, which has the goal of establishing a common power exchange in the Nordic and Baltic areas to improve competition and secure natural gas supply. The cost of the investment is estimated to be around 250 million euros, from which 75 % i.e. 187.5 million euros is funded by European Commission. In the end, 30 million euros is left for the Finnish government to invest in the project. The project is estimated to be complete in year 2020. (Baltic Connector)

Illustration 2, cont. From a case study 2017 for this course (N. N.):According to meta-analysis made by Labandeira et al. (2015), long-term elasticity is between -0.614 to -1.25, which is elastic relative to other fossil fuels. The short-term elasticity is naturally more inelastic, -0.249. The average of the long-term elasticities is -0.932. The increased competition of gas supply has already declined the prices in the Baltic area, so it is likely that the natural gas prices in Finland will also decrease. The price change is assumed to be -0.0058€ (the difference between the Finnish price 0.0296 €/kWh and the Estonian price 0.0238 €/kWh in 2017) (Eurostat, 2017). The taxation and levies are assumed to stay unchanged.

Price Elasticity of Demand	Change in CS
-0,932	€154 315 714
-1,25	€158 721 213
-0,614	€149 910 215
-0,249	€144 853 589

Problems with this quick and dirty approach:

- the estimate depends heavily on the functional form assumed
- external validity: are the estimates obtained elsewhere valid here?
- internal validity: much more information about the households would be necessary

But applied economists often use this approach given the time and data constraints. Better if the demand can be estimated with richer data

3. Indirect valuation: How to measure impacts that are not directly priced in the market?

Examples

- Building noise barriers on highways – what are the monetary gains?
- Workplace safety regulations and speed limits save lives – how to quantify such savings?
- Urban planning generates a versatile set of housing externalities – can we put a price tag on them?
    - Impact of rental controls on housing market externalities; Author, Palmer and Pathak, JPE 2014.
    - Neighborhood revitalization programs and their spillover benefits; Rossi-Hansberg, Sarten and Owen, JPE 2013.

Indirect valuation: main approaches

Revealed preference: Indirect market valuation revealed by data on observed behavior

- quasi-experiments
- hedonic regressions
- imputed valuations from trade-offs that people face

Stated preference: Surveys

- How much consumers value a new train line? Consultants' bread and butter..

Hedonic pricing: The hedonic price method (the hedonic regression method) can be used to value an attribute, or a change in an attribute, whenever its value is capitalized into the price of an asset, such as houses or salaries. It consists of two steps but the second is conceptually problematic and ignored here. Hedonic price function can be written as

$$P = F(C_1, C_2, ...C_k, N_1, ..., N_n) \tag{1}$$

where C_i could be the house characteristics and N_j the neighborhood characteristics. The change in the price of a house that results from a unit change in a particular attribute (i.e., the slope) is called the hedonic price, implicit price, or rent differential of the attribute. In a well-functioning market, the hedonic price can naturally be interpreted as the additional cost of purchasing a house that is marginally better in terms of a particular attribute.

Exercise: assume Cobb-Douglas for $F(.)$ and

- What is the expression for the hedonic price of an attribute?
- Find a linear regression model that can be, in principle, estimated by OLS

Hedonic pricing illustration: There is an emerging literature addressing if consumers can evaluate the costs of using the house. For example, the energy efficiency and energy technology choices should capitalize into the house price. Policy makers think that this is not the case:

- Programs to deal with inefficient choices: BREEM UK, LEED US, EPBD EU. These are effectively labelling programs that help the consumers to make informed choices.
- "labeled" houses trade with premium: Eichholtz, Kok, and Quigley, 2010; Kok, McGraw, and Quigley, 2011; Kahn and Kok, 2013; Eichholtz, Kok, and Quigley, 2013; Kahn, Kok, Quigley, 2014
- Finnish case: download paper *here*, and presentation *here*

Imputed valuations from the trade-offs that people face: the Value of Statistical Life, VSL: How much would individuals sacrifice to achieve a small reduction in the probability of death during a given period of time? How much compensation would individuals require to accept a small increase in that probability? These are reasonable economic questions, because many regulations result in very small changes in individuals' mortality risks.

$$VSL = \frac{WTP}{\Delta Risk} \tag{2}$$

- For example, $VSL = \$6 million$, consistent with the meta-analysis of previous estimates
- An illustration of an estimate from a change in speed limits, Ashenfelter and Greenstone, 2004, JPE.

Imputed valuations from trade-offs that people face: estimating changes in demand and supply

Fundamentally, policies change tradeoffs in markets, and thus demand and supply in the market. The reading illustrates one method for inferring how the market values the change.

1. estimate how demand (X^D) and supply (X^S) covariates impact the price (P) and quantity (Q)

$$P = \alpha_0 + \alpha_1 X^D + \alpha_2 X^S + u, Q = \beta_0 + \beta_1 X^D + \beta_2 X^S + v$$

2. use the above estimates together with information on demand and supply previous literature to identify how much the demand (valuation) has changed.

Let us see more precisely how this works below.

To pin down changes in WTP, let C denote the unobservable characteristic that we are interested in. Firms or policies may directly affect this characteristic. Let q^d be the quantity demanded, q^s is the quantity supplied, and p is the price. The error terms (u, v) are shifters of the demand and supply schedules on the quantity-price plane:

$$q^d = \alpha_0 - \alpha_1 p - \gamma C + u$$
$$q^s = \beta_0 + \beta_1 p + v$$
$$q^d = q^s$$

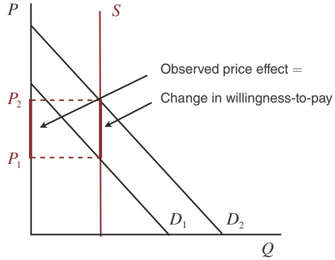
Market equilibrium:

$$p = \frac{\alpha_0 - \beta_0}{\alpha_1 + \beta_1} - \underbrace{\frac{\gamma}{\alpha_1 + \beta_1}}_{G} C + \frac{u - v}{\alpha_1 + \beta_1}$$

Market equilibrium:

$$p = \frac{\alpha_0 - \beta_0}{\alpha_1 + \beta_1} - \underbrace{\frac{\gamma}{\alpha_1 + \beta_1}}_{G} C + \frac{u - v}{\alpha_1 + \beta_1}$$

- The price reflects how consumers value C. So can we estimate WTP from the data by regressing prices on data about C? We can estimate the contribution of the characteristic (if we have measures for it as in the reading) to the price but this is not enough to identify changes in WTP. The next page Figure explains.
- Two ways forward:
  - (i) Use external information about demand or supply elasticities to identify WTP. This is done in the paper.
  - (ii) Identify demand and supply directly, for example, through demand or supply shifters as instruments. To be discussed below.



The idea is to estimate how the usage cost contributes to the equilibrium price of the car. Then, using external information about the slopes of the curves, one may try to quantify the willingness to pay for the fuel economy. The difficulty is to keep "all else equal" but the fuel cost. See the next page for results from Busse et al., 2013 AER.

The results

TABLE 3—GASOLINE PRICE COEFFICIENTS FROM NEW CAR PRICE SPECIFICATION

Variable	Coefficient	SE
GasolinePrice × MPG Quart 1 (lowest fuel economy)	−250***	(72)
GasolinePrice × MPG Quart 2	−96***	(37)
GasolinePrice × MPG Quart 3	−11	(26)
GasolinePrice × MPG Quart 4 (highest fuel economy)	104**	(47)

TABLE 4—GASOLINE PRICE COEFFICIENTS FROM USED CAR PRICE SPECIFICATION

Variable	Coefficient	SE	Coefficient	SE
GasolinePrice × MPG Quart 1 (lowest fuel economy)	−1,182***	(42)	−783***	(49)
GasolinePrice × MPG Quart 2	−101	(62)	118**	(54)
GasolinePrice × MPG Quart 3	468***	(36)	369***	(33)
GasolinePrice × MPG Quart 4 (highest fuel economy)	763***	(44)	360***	(36)
Depreciation varies by	Segment × PADD		MPG Quartile × PADD	

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

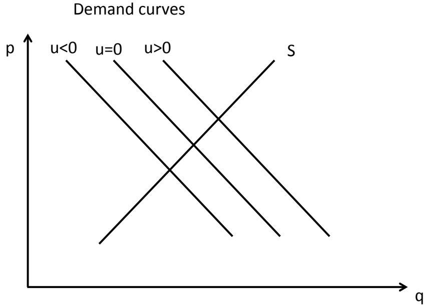
estimates indicate that a \$1 increase in the price of gasoline is associated with a lower negotiated price of cars in the lowest fuel economy quartile (by \$250). Higher price of cars in the highest fuel economy quartile (by \$104), a relative price difference of \$354.

Second approach: If we have many different observations of prices and quantities, we can apply econometric methods to estimate the entire demand curve, which then can be used in policy impact assessment. However, the demand cannot be estimated separately from supply. Set $C = 0$ to simplify and consider the following model

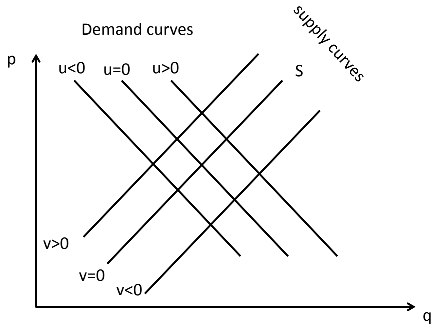
$$q_i^d = \alpha_0 + \alpha_1 p_i + u_i \tag{3}$$
$$q_i^s = \beta_0 + \beta_1 p_i + v_i \tag{4}$$
$$q_i^d = q_i^s \tag{5}$$

where i indexes the observation (period i for example), q_i^d is the quantity demanded, q_i^s is the quantity supplied, and p_i is the price. The error terms u_i, v_i are shifters of the demand and supply schedules on the quantity-price plane.

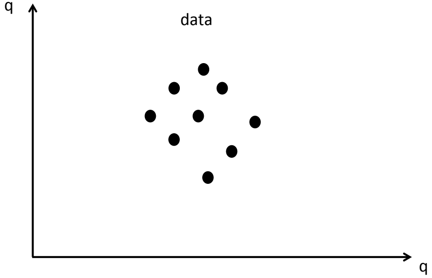
Usually data is a collection of price quantity pairs (q_i, p_i) for $i = 1, ..., n$ where n is the number of observations. Since we do not observe u_i, v_i, we cannot tell if a change quantity and price is due to a demand or supply shift.



Demand shifts



demand and supply shifts



The resulting data

Solution: We can estimate one of the curves if we can find observable factors that shift the other curve. For example, a supply shifter could be temperature or rainfall (relevant for harvest, for example). The supply becomes

$$q_i^s = \beta_0 + \beta_1 p_i + \beta_2 x_i + \epsilon_i \tag{6}$$

where is x_i is the temperature and ϵ_i is the remaining error term.

Solution: We then solve for the equilibrium price

$$p_i = \frac{\beta_0 - \alpha_0}{\alpha_1 - \beta_1} + \frac{\beta_2}{\alpha_1 - \beta_1} x_i + \frac{\epsilon_i - u_i}{\alpha_1 - \beta_1} \tag{7}$$

Plug this into the demand to see the correlation between temperature and the demanded equilibrium quantity $q_i^d = q_i$

$$cov(x_i, q_i) = \alpha_1 cov(x_i, p_i) \tag{8}$$

$$\Rightarrow \alpha_1 = \frac{cov(x_i, q_i)}{cov(x_i, p_i)} \tag{9}$$

This is the estimator for the price coefficient in the demand curve. Econometrics packages such as STATA have built in procedures for estimations using such "Instrumental" variables (temperature here).