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ECONOMICS OF TOBACCO TOOLKIT

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Tool 3. Demand Analysis

Economic Analysis of Tobacco Demand

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DRAFT

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I. Introduction

The tobacco epidemic is a worldwide phenomenon with significantly destructive effects on developing, transitional, and industrialized nations. The first scientific evidence on the health consequences of tobacco consumption—specifically, smoking—was discovered in industrialized nations. As a result, the economic analysis of tobacco control issues began and was developed in these countries.

Due to the origin of such research techniques, the English language literature is dominated by contributions from the United States. However, a new generation of economists and other analysts in low- and middle-income countries is developing programs of research into economic issues around tobacco control tailored to their own particular situations. This tool, along with the others in this series, is intended to assist such research initiatives.

Purpose of this Tool

This tool attempts to explain the process of analysis of demand for tobacco products as simply as possible. It includes discussions of basic economic and analysis principles (written for non-specialists such as policy makers and analysts) and more advanced technical points (intended for use by the economists and econometricians who will undertake the actual demand analysis).

This tool addresses the analysis of retail demand for tobacco products by individual consumers.

Analysis of demand for tobacco products necessarily focuses on retail demand, not the market in tobacco leaf or wholesale trade in cigarettes. This is because the profits of multinational tobacco companies, and hence the momentum of the global tobacco epidemic, are driven ultimately by retail demand for tobacco products by individuals. This tool, therefore, covers analysis of retail demand for tobacco products by individual consumers.

Consumption of tobacco products includes both smoked categories (e.g., cigarettes, hand-rolled tobacco, pipe tobacco, cigars, *bidis*, *kreteks*, etc.) and smokeless types (such as snuff and chewing tobacco). In industrialized countries, cigarettes disproportionately influence tobacco epidemics. There are two reasons: since the early 20th century, cigarette smoking is the leading form of tobacco consumption; further, smoking tobacco products causes disproportionately far more disease and death than chewing or inhaling tobacco. By contrast, in developing countries cigarette substitutes (in the form of other smoked and smokeless tobacco products and non-tobacco smoked substances) have much greater importance in local markets.

Given such mixed market importance and use of cigarettes and non-cigarette products, this tool attempts to focus on demand for tobacco products *as a whole*, making allowance for differences in category of tobacco products (or their substitutes or complements) where necessary. For both health and economics reasons, however, tobacco control initiatives should continue to focus primarily on the consumption of smoked rather than smokeless tobacco products for the foreseeable future.

Who Should Use this Tool

This tool contains information for several different readers. Those who are *not* specialists in tobacco issues, such as policy makers and analysts, will appreciate the coverage of basic principles involved in conducting demand analysis of tobacco products. Researchers should find the inclusion of literature references and discussion of theory helpful. Economists and econometricians will appreciate the bulk of this tool, wherein the step-by-step technical methods to undertake the actual demand analysis are presented over several sections.

How to Use this Tool

This tool discusses and presents, in technical detail, each of the steps necessary to conduct an economic demand analysis on tobacco products. In addition, the reader is presented the fundamentals of demand analysis, including its purpose, assumptions, and requirements. The reader is also referred, both within the chapters and extensively in the last chapter, to additional literature on issues that cannot be adequately addressed in this tool.

As a way of introduction, the **Define the Objectives of the Analysis** chapter summarizes the objectives of the demand analysis study, the reasons for undertaking it, what the results are used for, and the typical structure and resource requirements of such a study.

The **Conduct Background Research** chapter emphasizes the importance of determining the characteristics of the tobacco product market in a particular country or geographic region.

A critically important part of the analysis process is presented in the **Build the Data Set** chapter, which discusses how to choose variables and prepare data for regression analysis, and highlights the importance of the type and quality of data in determining the use of analytical techniques.

The **Choose the Demand Model** chapter details the first step in conducting an econometric analysis, and discusses such issues as the identification problem, demand model types, and functional form.

The second step is addressed in the **Specify the Demand Function** chapter, in which options include conventional and addictive models for aggregate annual, quarterly, and monthly time-series data. This chapter also summarizes salient issues involved in econometric analysis of demand using cross-sectional and pooled time-series of cross-sectional data.

Meaningful interpretation of the demand analysis results is urged in the **Review and Understand the Results** chapter. This chapter outlines the calculation of elasticities of demand, suggests the expected nature of estimation results for each of the key variables, and explains these expectations in terms of prior research into the nature of the variables and the mechanisms involved in their impact on demand.

The chapter **Another Demand Model: Error Correction Models and Diagnostic Tests** briefly covers variable stationarity, cointegration, and the use of error correction models, alternative regression techniques, and specification and diagnostic tests. This chapter also contains definitions and background information with which every reader should become familiar. Further, this chapter includes the assumptions made by the author, as well as the requirements expected of the reader to best utilize this tool.

The conclusion is presented in the **Disseminate the Research Findings** chapter, which covers the presentation of results and their policy implications in research reports, structured specifically to suit the information requirements of different audience sub-groups.

Readers interested in additional research and empirical studies on demand analysis should refer to the **Additional References** chapter.

II. Define the Objectives of the Analysis

Before commencing an analytical study of the demand for tobacco products, it is essential to define clearly the purpose and objectives of the research, plan the analytical process, and ensure that adequate resources are secured for the study. Only a brief overview of these tasks is addressed here. Refer to **Tool 1. Political Economy Issues** for detailed coverage of analytical studies and their importance in tobacco control efforts.

The Reason for Analysis of Demand

The fundamental reason to analyze the demand for tobacco products is to achieve sufficient understanding of the ways in which demand is determined. Knowing this, demand can then be influenced—or more appropriately, reduced.

In turn, the reasons to intervene in the market for tobacco products stem from the destructive nature of tobacco consumption. Smoking is the single largest preventable cause of premature death in industrialized countries. This epidemic is quickly gaining similar status in the developing world as well, even though tobacco-related morbidity and mortality in many low- and middle-income countries are currently outweighed by other causes. Strictly from a health perspective, there is a strong reason to intervene and reduce the "anti-health" behavior of tobacco consumption in order to reduce the current and future toll in tobacco-related illness and death.

The Economic Case for Demand Intervention

In economic terms, the principle of consumer sovereignty holds that individuals know what products are in their best interests to consume. Provided consumers know the risks concerned and internalize all the costs and benefits involved, private consumption decisions result in the most efficient allocation of society's scarce resources. However, the tobacco market is characterized by three market failures that result in economic inefficiencies and may therefore justify public intervention:

1. *There is "information failure" about the health risks of smoking*. Because the tobacco industry has concealed and distorted information on the health risks of smoking, and because there is a delay between starting to smoke and the onset of tobacco-related disease, consumers tend to underestimate the health risks involved. While this underestimation is particularly prevalent in low- and middle-income countries, consumers in all countries may not grasp the scale of the health risks of smoking, even when they have been informed of them, and may not apply this knowledge to themselves.
2. *There is "information failure" about the addictive nature of tobacco consumption*. Smokers acquire psychological addiction (habit formation) to the act of smoking, and physical addiction to nicotine. Physical addiction in particular means that the effort and discomfort involved in quitting smoking are significant. Many prospective smokers, and particularly adolescents, underestimate the risks of becoming addicted to nicotine, and once addicted face high costs in trying to quit. These two information failures result in high private costs of death and disability for smokers.
3. *Smoking imposes external costs on non-smokers*. Direct physical costs to non-smokers include the health impacts and nuisance value of environmental tobacco smoke (e.g., passive smoking) and the greater risk of fire and property damage. Financial costs borne by people, whether or not they are exposed to tobacco smoke, include tobacco-related public health care costs and cross-subsidization of tobacco-related private health care costs. In addition, "caring externalities" include the emotional suffering of non-smokers due to the illness and death of smokers.

In sum, the existence of ignored internal costs (in the form of harm to smokers themselves) and external costs (in the form of harm to others) justifies both government intervention and research on the effects and benefits of alternative policies to limit demand of addictive substances such as tobacco. Analysis of demand for tobacco products is a crucial component of such a research program.

Analysis of Demand for the Policy Maker

Tobacco products are available to consumers for a price, and an issue of great interest to tobacco control advocates (and the tobacco industry) is to what extent are consumers willing to buy those tobacco products. For instance, the willingness to buy is strongly influenced by such characteristics as the consumer's sense of value, income level, and taste (which is influenced by social, cultural, and other demographic variables, including exposure to advertising). So the fundamental principle in analysis of demand for tobacco products is not only that these factors (among others) influence an individual's propensity to consume a particular tobacco product, but that they influence the propensity to consume *at a particular price*. In other words, demand factors influence the price-responsiveness of consumers, and a major role of analysis of demand for tobacco products is to investigate and explain *how* and *to what extent* this price-responsiveness is influenced by *which* demand factors.

Thus the role of an analysis of demand for tobacco products is to *qualitatively* explain the relationship between certain demand factors and the price-responsiveness of consumers and their demand for tobacco products, and then to *quantify* that relationship using econometric techniques. The estimates of the parameters of demand for tobacco products can be used to predict the direction and degree of impact on demand of such control measures that:

- increase the excise or *ad valorem* tax on tobacco products;
- impose restrictions on smoking in public places and private workplaces;
- regulate tobacco product advertising;
- restrict sales of tobacco products to minors;
- develop and disseminate information on the health risks of smoking through "counter-advertising" campaigns; and
- provide access to smoking cessation programs and nicotine replacement therapy.

The information from these predictions can be provided to policy makers and others concerned with tobacco control.

Design an Analysis of Demand Study

Components of a Study

The functional framework of an analysis of demand study includes the following components:

1. A design phase to design the study and develop structures and management procedures.
2. A data preparation phase to:
   - gather background information and the data to be used for detailed analysis;
   - evaluate and clean the data; and
   - transform the data.
3. An econometric analysis phase in which to:
   - specify the econometric models;
   - select and implement econometric techniques;

    - perform the econometric analysis;
    - test the results; and
    - if necessary, correct the model specifications and perform the analysis again.

4. A dissemination phase in order to communicate the results and findings of the study to all interested parties, particularly those organizations that originally commissioned the study.

The Nature of Econometric Analysis

Econometrics is a useful tool for measuring the influence of a range of factors on the demand for tobacco products. One major drawback is that it involves complex and sophisticated techniques often only available to economic specialists. Therefore, to get the strongest results out of the demand analysis study, keep in mind the following:

- The validity and accuracy of econometric analysis depends critically on the care with which it is conducted. It is important that economists with adequate competence in and experience of applied econometric analysis conduct the analysis of demand for tobacco products.
- There is a need for pragmatism in designing the demand analysis. For example, compromises may be made regarding the inclusion of variables in the demand specification, or the quality and availability of the data required may be balanced against the likelihood of specification error resulting from omitting a significant variable. In such instances, a researcher's experience and clear-headed judgement is particularly important.
- The analysis process should be documented in detail. This helps researchers cope with changes in data or estimation technique that are forced upon them by measurement or specification problems. It also lets them confidently answer questions from analysts, policy makers, and lobbyists regarding the data used, the econometric techniques applied, and problems they encountered and solved.

Resources Required

The resources required for the study will include the following:

- an economics graduate with competence in, and some applied experience of, econometric analysis;
- a personal computer;
- a good spreadsheet software package;
- an up-to-date econometrics software package (such as SAS, STATA, or SPSS) that can, for example, handle relatively recent innovations such as the Johansen cointegration procedure;

- data on tobacco product demand variables, in sufficiently numerous observations and of sufficient accuracy, to meet the analytical requirements of the study; and
- an adequate budget of both time and financial support to guarantee the effective use of the above resources.

Summary

Below is a list of questions and concerns to address that can act as a checklist for researchers, analysts, and policy makers initiating economic analysis of demand for tobacco products. With the aid of this tool, the answers to these questions should be clarified and formalized during the planning of the study, and then communicated clearly to all researchers involved.

1. What is the overall objective of the analysis?
2. What are the fundamental research questions the analysis will attempt to answer?
3. What are the intended outputs of the analysis?
4. What are the required data inputs?
5. What are the required resources to conduct the analysis?
6. Who will coordinate the research?
7. What agencies with appropriate experience can review and provide constructive feedback on the research?
8. Who is the target audience for the results of the study?
9. How will the research results be disseminated?

References and Additional Information

The following are sources of information to refer to for background discussions of tobacco demand. See the **Additional References** chapter for a complete description of these and other sources.

World Bank (1999) provide a useful summary of the economic rationale for intervention in the tobacco market, and discuss ways in which governments may intervene.

Chaloupka and Warner (1999a) offer an excellent introduction to the main economic issues in tobacco control, summarizing salient research into the impact of price, advertising, smoking restrictions, and other factors on demand for tobacco products.

III. Conduct Background Research

> *One of the most demanding disciplines in flight test was to accustom yourself to making precise readings from the control panel in the same moment that you were pushing the outside of the envelope. This young man put his [aircraft] into the test dive and was still reading out the figures, with diligence and precision and great discipline, when he augered into the oyster flats and was burnt beyond recognition…and the [other pilots] remarked that the departed was a swell guy and a brilliant student of flying; a little too* much *of a student, in fact; he hadn't bothered to look out the window at the real world soon enough.*
>
> *—Tom Wolfe, "The Right Stuff"*

Economic theory dictates the specification of econometric models of the demand for tobacco products, within pragmatic limits—compromises must be made, for example, between theoretical considerations and the availability and quality of data. In this regard, it is essential to avoid the pitfalls of data mining (i.e., avoid applying an arbitrary succession of variables to econometric analysis of data on tobacco product consumption in the hope of finding a satisfactory explanation of the latter).

However, because every country or other geographical unit is different and faces a unique and distinct tobacco epidemic, detailed knowledge of the tobacco situation within a country should inform both the theoretical modeling and econometric analysis of demand for tobacco products. For example:

- Cross-border cigarette smuggling can play a major role in a country, in which case researchers are forewarned to control the data for its effects in order to avoid biased estimates.
- A particular religion that frowns on tobacco use might be well represented in certain parts of a country, in which case this negative influence on per capita tobacco product consumption should be controlled for.
- If substitutes for smoked tobacco products, such as hand-rolled cigarette tobacco or marijuana, are cheap and

easily available in a country, poorer citizens and youth may substitute these for cigarettes if the price of the latter rises significantly. This possibility should be taken into account to the extent that data availability allows.

Prior research should inform the economic analysis of demand of the social, economic, and institutional characteristics of the market for tobacco products in a country. In other words, the economists and econometricians conducting the analysis should first discover and identify the characteristics of the tobacco market in their own country. Relevant prior research across all academic disciplines should also be identified to provide the necessary background information. If information is still lacking, initiate a rapid appraisal-type research study into the salient characteristics of the domestic tobacco market, consumers, tobacco companies, and so on.

The advantage of detailed background research is that it helps one:

- evaluate the econometric results of the analysis, and judge whether the model specification and/or other parameters should be modified; and
- explain the econometric results in the research report(s) submitted to colleagues, other analysts, and policy makers.

IV. Build the Data Set

This chapter outlines the difficulties in choosing appropriate data variables for inclusion in demand models, and suggests ways of preparing the variables selected in order to achieve the most valid results from the analysis. While international research experience in this regard is useful, a clear and detailed understanding of one's own country situation is the best guide to the selection and preparation of data variables.

Building the data set is a time-consuming part of the analysis process, as it involves the following activities:

- choose the variables to be included in the model of demand;
- evaluate, screen, and clean the data;
- prepare the data for regression analysis; and
- conduct exploratory data analysis.

Discussion of data in this tool focuses on the most appropriate type of data for analyzing tobacco product demand, and the necessary procedures to make the data variables useable once they are selected and obtained. See **Tool 2. Data** for more detailed information on potential sources of data for use in analyzing economic aspects of tobacco control, including the demand for tobacco products.

Choose the Variables

Data Availability

It is critically important to ascertain:

- the availability of data series for each of the possible variables that may be included in the demand analysis; and
- the characteristics of these data series (e.g., how many observations are covered? how was the data gathered and captured? how accurate is it likely to be? how high is the incidence of missing observations?).

Researchers are likely to face challenges in assembling data for demand analyses. Data for a potentially significant variable, and which should therefore be included in demand model specifications, may not be available or may be of dubious accuracy. As Chaloupka, Grossman *et al* (1999) point out:

> *Economists generally rely on large survey and aggregate data collected by others for different purposes that often do not contain everything that would ideally be included. In addition, the econometric analyses employing these data must attempt to control for the variety of other factors that are also likely to affect behaviour and that are varying in the real world from which these data are drawn but for which good measures are often not available.*

Data Types

The type of data to assemble determines the specification of the demand model estimated, the econometric techniques used for estimation, the measurement and specification problems encountered, and ultimately the nature of the questions that can be answered by the econometric analysis. Data types relevant to demand analysis include:

1. aggregate time-series data;
2. cross-sectional data, including:
   - aggregate cross-sectional data, and
   - individual-level cross-sectional data from large surveys;
3. time-series of cross-sectional data (pooled, panel, or longitudinal data).

This tool focuses on the use of aggregate time-series data, in which “aggregate” means “total” (i.e., an aggregate time-series consists of a time-series of the total values of a particular variable for the particular country or region as a whole). Further, per capita measures of tobacco product consumption, income, and other variables are often used in demand analysis, and are usually *based on* aggregate values. For example, the annual per capita cigarette consumption of persons aged 15 and over in a country is typically calculated by dividing total annual cigarette sales by the total number of people aged 15 and over as obtained from the population census. Hence, per capita data series are discussed along with aggregate data series.

There are two important reasons why researchers in certain countries may have to rely on aggregate time-series data to analyze the demand for tobacco products:

- In many low- and middle-income countries, individual-level data sets from large household and other surveys are not commonly available at a reasonable cost. If they are available, they may not include much data on respondents’ consumption of tobacco products.

- In most low- and middle-income countries, cross-sectional data is unlikely to feature significant variance in crucial independent variables such as retail price. Most studies using cross-sectional data are undertaken in the United States, which has a "fiscal federalist" constitution wherein state and local governments have the power to levy their own excise taxes on tobacco products. This makes for sufficient variation in retail prices between states and cities to allow analysis of cross-sectional data.

  By contrast, few low- and middle-income countries are large enough to have federal constitutions, let alone fiscal federalism. Excise taxes are typically levied by the central government at uniform rates for the whole country. Further, tobacco product manufacturers are unlikely to charge widely differing wholesale prices between sub-national geographic areas. Even if they did, transport infrastructures are usually so poor that transport costs entirely eliminate both the incentive for tobacco product wholesalers to arbitrage between areas of high and low wholesale price, and the retail price differentials. Hence, in such countries researchers must rely on the price variation inherent in time-series data.

Accordingly, chapters 6–8 of this tool deal with the analysis of aggregate time-series data, while the *Cross-Sectional Data* and *Pooled Time-Series and Cross-Sectional Data* sections of the **Specify the Demand Function** chapter briefly discuss using individual-level cross-sectional data and individual-level time-series of cross-sectional (longitudinal) data, assuming that these are available.

In some countries, aggregate time-series data may not be available for a time period long enough to provide a sample of the necessary size to estimate a demand model. In this case, pooled time-series of aggregate cross-sectional data can be a useful substitute. For example, larger low- and middle-income countries may produce data on tobacco product consumption on the basis of sub-national regions (e.g., by state or province). If these data are available on a quarterly basis for a time period of several years, the pooled data sample may be large enough to allow demand estimation.

Prepare the Data

Data must be captured on computer in a manageable form. The most useful format is a computerized spreadsheet, for example Microsoft® Excel or Lotus® 1-2-3, as this allows easy and efficient manipulation and transformation of the data. Spreadsheet files can also be used to input the data into most econometric software packages. Be sure to conduct tests to determine the accuracy of the data capture or transcription process.

Data Cleaning and Preliminary Examination

Data must be screened and cleaned of missing or incorrect values and other errors. See **Tool 2. Data** for guidelines on the specific processes involved.

It is important to check the validity of data before undertaking regression analysis, particularly for the following reasons:

- The method of data collection is known to be of doubtful accuracy.
- Problems with the accuracy of data from the same source(s) have been encountered in other analyses.
- The institution tasked with collecting and publishing the data is known to suffer from severe capacity problems.

One of the most useful methods of checking the plausibility of data is to graph each variable. This is one of the quickest and most effective ways of spotting outliers in the data, or movements or disjunctures in the data series that appear strange or implausible. For example, does tobacco product consumption increase or decrease unrealistically rapidly during a particular sub-period? Are the trends in price data plausible?

Another important reason for graphing each data variable is to understand the functional form it follows most closely (e.g., linear or logarithmic) in order to decide which forms are preferable in the demand equation(s) to be estimated. See the *Select the Functional Form* section in the **Choose the Demand Model** chapter for further discussion of this process.

Preparing the Data Variables

Tobacco Product Quantities

Data are required on the aggregate quantities of the relevant tobacco product(s) consumed within the particular time periods (month, quarter, or year) covered in the demand analysis. It is preferable to obtain data on *consumption* rather than *sales* of tobacco products, particularly if smuggling into the country is a significant problem (in which case sales figures considerably understate true consumption).

In most prior studies of the demand for tobacco products, the dependent variable is cigarette consumption per adult within the relevant time period in packs of 20 or in number of individual cigarettes, for the following reasons:

- The tobacco product used is cigarettes, as they are the major tobacco product health hazard in most countries and therefore most relevant to study.
- A per capita consumption measure is used to control for the influence of population growth on aggregate sales of tobacco products. If aggregate cigarette consumption figures are used instead, the influence of population growth is factored by other estimators, particularly the time trend variable (unless the population above the

threshold age is included as an extra independent variable).

- Data on cigarette sales are typically used as a proxy for cigarette consumption, with various attempts to control for additional consumption due to smuggling.
- Arguably, it is more accurate to use average nicotine intake per person (or a proxy, such as tobacco content consumed per person) because this controls for changes in the tobacco content (and hence the nicotine content) of cigarettes over time. This in turn provides an allowance for the fact that, as the average nicotine delivery of cigarettes has fallen during the last 30 years, many long-term smokers have compensated by increasing the number of cigarettes they smoke. Such compensating behavior tends to artificially inflate cigarette sales figures, biasing downward any estimate of the impact of price and other control variables. However, data on cigarette sales are more easily available in developing countries than data on the tobacco and nicotine content of particular cigarette brands and the market shares of particular brands.

In low- and middle-income countries where consumption of *bidis*, *kreteks*, and hand-rolled tobacco is significant, the weight of tobacco consumed per capita per time period naturally provides a more accurate measure of tobacco product consumption. This assumes data are available on the quantities consumed or sold, and a plausible average weight can be used to convert such quantities into pounds or kilograms.

In all instances, the definition and unit of measurement of the tobacco product quantity used in the demand analysis must be clearly stated by researchers. For example, if consumption is measured in packs of cigarettes sold, researchers must state clearly what is assumed to be the average number of cigarettes per pack. If consumption is measured in weight of tobacco consumed per capita, the assumptions and arithmetic manipulations made in arriving at this data series need to be explained clearly.

To calculate per capita consumption, data are required on the size of the relevant population. Prior studies have generally assumed that significant consumption of tobacco products begins in late adolescence, thus providing one definition of a population. However, in many low- and middle-income countries, inadequate and/or poorly enforced restrictions on youths' access to tobacco products means that significant prevalence of smoking and other tobacco product consumption starts at an earlier age. Regardless of the threshold age, researchers need reasonably accurate data on the size of the population above that age.

In some countries it is difficult to obtain accurate data on total retail sales of cigarettes and other tobacco products. The most common way of resolving this problem is to collect official data on the total excise tax revenue obtained from tobacco product sales. This data is then divided by the average tax component per pack to yield the total quantity of cigarettes sold. However, there are two potential drawbacks to this approach:

- Differences in retail prices between countries can result in smuggling (both large-scale, "organized" smuggling and small-scale, informal "bootlegging") from lower-tax countries into higher-tax countries. Using official excise tax data will therefore likely overstate cigarette consumption in lower-tax countries, and underestimate it in higher-tax countries, producing upwardly-biased estimates of the impact of retail price on demand. Refer to **Tool 7. Smuggling** for a more detailed discussion on smuggling and methods to account for it.
- Data on excise tax receipts are usually compiled from wholesale rather than retail transactions (i.e., from transactions in which wholesalers buy tobacco products from manufacturers). The timing and volume of these transactions are influenced by seasonal marketing patterns of manufacturers, and introduces an artificial element of "seasonality" into monthly and quarterly excise tax data, and hence into tobacco product demand figures. Methods of dealing with this problem (if quarterly or monthly data are being used) by using dummy variables are discussed in the *Demand Specifications for Quarterly Time-Series Data* and *Demand Specifications for Monthly Time-Series Data* sections of the **Specify the Demand Function** chapter. Where possible, data on tobacco product quantities consumed and demanded should *not* be seasonally adjusted, since the filters used for this adjustment often distort the underlying properties of the data. This distortion is especially problematic if the data are non-stationary and cointegration techniques have to be applied (see the *Apply Tests for Non-Stationarity and Cointegration, and Specify Error-Correction Models* section in the **Another Demand Model** chapter).

Price

In many countries, the retail price of tobacco products includes either a specific or *ad valorem* excise tax component. (Refer to **Tool 4: Design and Administration** for an in-depth discussion on excise taxes.) The relationship between tax and price affects the ultimate price of tobacco products, and is therefore an important topic of consideration for tobacco control policy. However, it is not directly relevant when quantifying the impact on demand of price and other variables. This is because price, as treated for the purposes of this tool, is the ultimate value confronting the consumer, inclusive of any excise or *ad valorem* tax, sales tax, value-added tax, or other levy.

Exceptions to this principle occur when the tax component of retail price is used either as a proxy (if retail price data are unavailable), or as an instrumental variable (if retail price is found to be endogenous). In this case, the necessary adjustments to price elasticity estimates must be made, as tax elasticities of demand understate the true price elasticities to the extent that tax is a proportion of retail price. For example, in estimating the impact of tobacco excise taxes on demand for tobacco products in Papua New Guinea, Chapman and Richardson (1990) used data on the excise taxes themselves, rather than on price. Data on price for cigarettes and other tobacco products were not available, nor was information available on the relationship between excise taxes and price.

If sufficient data are available, retail tobacco product prices should be averaged over product sub-types (e.g., filter, plain cigarettes) and types of sales transaction (e.g., retail single pack, carton, vending machine), weighted by estimated market share in each case. There is likely to be substantial variation between the prices of product sub-types and the prices obtained in different types of transactions, and using a weighted average price provides a realistic idea of the actual retail price of tobacco products confronting prospective buyers.

Deflate price data to real terms, using the local Consumer Price Index (CPI) or the most appropriate available proxy.

Income

Deflate data on aggregate personal disposable income to real terms, using the CPI or the most appropriate available proxy. Data on population size over the threshold age should be used to calculate per capita personal disposable income values.

Advertising and Promotion

Modeling the impact of advertising and promotion expenditures on the demand for tobacco products is difficult, yet should be included as an independent variable if quarterly or monthly data are being used. If meaningful results are to be obtained from the inclusion of this variable, collect data on all media and forms of tobacco product advertising and promotion, including:

- Expenditures on traditional advertising in the cinema and on television, radio, billboards, and posters; in newspapers, magazines, and transit facilities; and (if possible) on the Internet.
- Expenditures on promotional activities such as promotional allowances to retailers; point-of-purchase materials; direct mail advertising; distribution of free samples, coupons, and specialty or novelty items; multiple pack promotions and retail value-added offers; endorsements; sponsorship of cultural, sporting, and other entertainment events; and sponsorship of community and other organizations.

This can prove a challenging task, particularly in countries where advertising and promotional expenditure data are not compiled by a central industry association or market research company. In addition, the measure of advertising used as an explanatory variable should be the ratio of advertising on the particular tobacco product to total advertising, in order to measure the weight of the former relative to the latter. This means that advertising data should also be collected on total expenditure in each of the above media.

In practice, however, such a rigorous approach is not practical if comprehensive and systematic data are difficult to obtain. Innovative approaches to this problem include that of Hu, Sung, and Keeler (1995), who used total pages of cigarette advertising in issues of *Life* magazine distributed in California as a representative sample of the tobacco industry media presence in that state. Advertising was modeled as an accumulated stock of cigarette advertisements per magazine issue for all previous quarters, depreciated by five percent per quarter, with a one-quarter lag between advertisements and initial impact.

See the *Advertising and Promotional Activity* subsection in the **Review and Understand the Results** chapter for a further discussion of incorporating such data into a model.

Health Information and "Counter-Advertising"

Modeling the impact of health information or counter-advertising campaigns on demand faces the same difficulties as for advertising and promotion. However, given that counter-advertising campaigns are usually run one-at-a-time and are typically focused on a much wider target audience than tobacco product marketing, it may be practical to use dummy variables rather than expenditure data to control for their influence.

Researchers confronted with data availability problems use other approaches besides dummy variables. For example, Hsieh, Hu, and Lin (1999) used the market share of newly introduced low-tar cigarettes in Taiwan during 1988–1996 as a proxy measure of the spread of anti-smoking information.

Smoking Restrictions

Researchers need to judge the average intensity of smoking restrictions applied in a country in order to develop an index of average smoking restrictiveness for the country as a whole, for each of the time periods under analysis. To produce this index, first calculate the intensity of smoking restrictions in each locality or province. (As a more feasible alternative, a representative sample of localities and/or provinces can be surveyed.) Measure the intensity of smoking restrictions with a numerical scale running from 0 (least intensive) to 1 (most intensive), in line with the methodology used by Wasserman *et al* (1991), as follows:

Score	Intensity of Smoking Restriction
0.00	No smoking restrictions in place.
0.25	Smoking restricted in one to three types of public place other than restaurants.
0.50	No restrictions on smoking in restaurants, but smoking restricted in at least four other types of public place.

Score	Intensity of Smoking Restriction
0.75	Smoking restricted in restaurants, but not private workplaces.
1.00	Smoking restricted in private workplaces.

If possible, weight the index of intensity for each locality by the proportion of the total population it contains. Then calculate the average index of intensity for the whole country for the year in question.

If the necessary data are not available for the computation of an index of intensity of any imposed smoking restrictions, use a dummy variable to control for their introduction.

References and Additional Information

The following are sources of information to refer to for background discussions of tobacco demand. See the **Additional References** chapter for a complete description of these and other sources.

> Stewart (1992) provides a classic critique of the quality and preparation of the data used in an econometric study. He comprehensively demolishes the credibility of an econometric analysis of the impact of tobacco advertising bans in OECD countries simply by highlighting errors and inconsistencies in the compilation of the data. The article provides a highly useful and salutary lesson for all those undertaking applied econometric research.

V. Choose the Demand Model

Determine the Identification Problem

The quantities and prices of products bought and sold in competitive markets are determined simultaneously (that is, price is endogenous). Failure to account for such simultaneous determination in regression analysis of demand for tobacco products results in biased estimates. However, if it is reasonable to assume that the supply of tobacco products is infinitely elastic (and hence that price is in essence exogenous), there is no identification problem—it is certain that every combination of price and quantity in the data lies on the demand curve.

In many low- and middle-income countries it may indeed be the case that the supply of tobacco products is infinitely elastic, particularly for those countries that must import the bulk of their tobacco leaf and/or manufactured tobacco products. Most countries are small relative to the global market for tobacco leaf and tobacco products, and tobacco companies allocate their (finite) supplies of both to the countries that pay the highest prices. Once the marginal demander of tobacco is not willing to pay these prices, supplies are shipped to another country. In these circumstances, supply within many countries can be characterized as infinitely elastic.

If it is *not* reasonable to assume that supply is infinitely elastic—in other words, if price is endogenous—either instrumental variable techniques or simultaneous equation modeling are applied. Simultaneous equation modeling of both demand and supply is not advisable, however, because of data availability problems and potential model specification difficulties. The necessary data on production costs of tobacco products (including cost of capital, raw material costs, etc.) may not be available, or may be inaccurate, and it is unlikely that tobacco companies themselves will voluntarily provide such data.

Moreover, while the literature includes several equally plausible models of the supply side of the tobacco product sector, these may not be appropriately specified for a particular country's tobacco product market. Using them can therefore bias the estimates obtained—the very problem that simultaneous equation modeling is intended to obviate. Researchers must judge for themselves the advisability of simultaneous equation versus other ways of modeling demand for and supply of tobacco products, depending on their specific circumstances.

Test for Price Endogeneity

Use Hausman's test (reference) to determine whether price is exogenous or endogenous, as follows:

1. Estimate an ordinary least squares (OLS) demand regression treating price as exogenous, giving a price coefficient of b.
2. Construct an instrumental variable p′ for price by regressing price on all other exogenous variables to obtain predicted values of p′.
3. Estimate a second OLS demand regression replacing price with the instrumental variable p′, obtaining a new "price" coefficient of b′.
4. Calculate the following statistic: $m = (b' - b)^2 / [\mathrm{var}(b') - \mathrm{var}(b)]$. Asymptotically, m follows a chi-squared distribution with one degree of freedom (d.f.).
5. The null hypothesis is that price is exogenous, and hence that there is no statistical difference between b and b′. To test this, look up the critical value of m at the one percent significance level for one d.f. from chi-squared tables. If m is greater than the critical value, the null hypothesis that price is exogenous must be rejected.

Find Instrumental Variables

The fundamental reason to look for instrumental variables is that the independent variable in question (in this instance, price) is correlated with the error term in the demand specification (in this case because price is endogenous). Hence, if price is endogenous it is necessary to find a variable correlated with price, but not correlated with the error term.

In practice it can be difficult to find suitable instrumental variables. Researchers must use their knowledge of the tobacco product market to find variables correlated with the particular independent variable, but which do not "belong" in the demand specification. When choosing between several potential instrumental variables, the one most highly correlated with the original independent variable is chosen in order to minimize the variance of the instrumental variable estimator as much as possible. Variables commonly used as instruments for the price of tobacco products include the excise tax component of retail price, the cost of tobacco, and lagged price.

Select the Demand Model Type

The basic models of tobacco product demand to choose from are:

- Conventional demand models, which are static (i.e., they examine the impact of explanatory variables on demand only within a single time period).
- Addictive demand models, which are dynamic (i.e., demand in a given time period is affected by demand in past or future periods, as well as by other explanatory variables operating within the current time period). Addictive demand models are further subdivided into models of *myopic addiction* and *rational addiction*.

In essence, addictive demand models contain the same independent variables as conventional demand models, but with the addition of future demand and/or past demand. Typical specifications of each of these three basic demand models are detailed in the *Demand Specifications for Annual Time-Series Data* section of the **Specify the Demand Function** chapter. The rationale underlying the myopic and rational addictive models is discussed in the *Nicotine Addiction and the Role of Past and Future Demand* subsection of the **Review and Understand the Results** chapter.

Select the Functional Form

Each of the basic models of demand, above, is applicable in either of the most commonly used functional forms:

- Linear, where the data observations for both dependent and independent variables are left as levels.
- Semi-log, which can be either
  - log-lin, where the dependent variable is transformed into logarithmic values of the original data observations, while the independent variables are left as levels.
  - lin-log, where the dependent variable observations are left as levels, while the independent variables are transformed into logarithmic values.
- Double-log (also known as log-log or log-linear), where logarithms are taken of both dependent and independent variables.

Theory offers very little practical guidance about the choice of functional form for demand model specification. One minor advantage of the double-log functional form over the linear form is that the estimated coefficients on price and income are, in effect, the price and income elasticities of demand. However, when using a linear specification, the elasticities are easily calculated from the values of the coefficients and data observations using the simple formulae provided in the *Calculate Elasticities of Demand* section of the **Review and Understand the Results** chapter. On the other hand, there are two drawbacks of the double-log model:

- It implies constant elasticities, which may not be a valid assumption for time-series data.

- Use of the double-log functional form can yield illogical results if the demand estimations are also being used to determine the optimal level of excise tax. Since the excise tax affects the size of consumers' surplus, the size of the pre-tax surplus is a key determinant of the potential tax yield of tobacco. A double-log specification of the demand function implies an infinite consumer surplus when the (absolute value of) price elasticity of demand is less than one. This in turn suggests that the product yields more tax revenue than a linear specification, and implies that tax revenue is a positive function of the tax rate. Consequently, do not choose double-log demand specifications if the results are going to be used to determine the optimal excise tax for tobacco products (Refer to **Tool 4: Design and Administration** for further discussion on excise taxes).

The semi-log functional forms are useful when preliminary examination of the data suggests that the dependent variable fits a logarithmic form, while the independent variables follow a linear form (or *vice versa*), helping to ensure a better fit of the demand specification. The semi-log form also has the advantage of not imposing the assumption of constant demand elasticities on the demand model implicit in the double-log specification.

It should be noted that the lin-log specification, like the double functional form, implies an infinite consumer surplus when the (absolute value of) price elasticity of demand is less than one. This can, therefore, yield illogical results when estimates are used in analysis of optimum tax revenue. The log-lin functional form does not incur this problem, as it implies a finite consumer surplus under the same conditions of price elasticity of demand.

The linear, semi-log, and double-log functional forms can be used in separate specifications, and the results compared. Methods of determining which functional form is the more appropriate are discussed in the *Administer Specification and Diagnostic Tests* section of the **Specify the Demand Function** chapter.

VI. Specify the Demand Function

This chapter contains typical demand specifications for aggregate time-series data, using both conventional and addictive demand models and linear and double-log functional forms. Further discussion on the rationale for including each of the specified independent variables, and the regression results to be expected, is presented in the *Expect Results for Quantitative Independent Variables* and the *Expect Results for Qualitative Independent Variables* sections of the **Review and Understand the Results** chapter. To make comparison easier, Table 3.1 includes examples of the demand specifications discussed.

Demand Specifications for Annual Time-Series Data

When using annual aggregate time-series data, it is preferable to keep the demand specification as simple as possible (i.e., use as few independent variables as possible) for the following reasons:

- The number of observations in annual data is probably small, and limiting the number of independent variables conserves degrees of freedom.
- There is likely to be a high degree of collinearity between independent variables in aggregate time-series data. The relevant rule of thumb—Klein's Rule—states that if the correlation between independent variables A and B is greater than the correlation between A (and/or B) and the dependent variable, then either A or B should be excluded from the model.

Dependent Variable

For the reasons discussed in the *Prepare the Data Variables* subsection of the **Build the Data Set** chapter, in all examples of model specification in this chapter it is assumed that the dependent variable is cigarette consumption per potential smoker within the relevant time period (month, quarter, or year). (Note that researchers must also define precisely the unit of

Table 3.1
Examples of Demand Model Specifications by Data Period, Type of Demand Model and Functional Form

Data Period/Model Type/ Functional Form†	Demand Specification‡	Equation Number
Annual/Conventional		
Linear	$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + \varepsilon_t$	3.1
Double-Log	$\ln Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + \varepsilon_t$	3.4
Log-Lin	$\ln Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + \varepsilon_t$	3.7
Lin-Log	$Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + \varepsilon_t$	3.10
Annual/Myopic Addiction		
Linear	$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6Q_{t-1} + \varepsilon_t$	3.2
Double-Log	$\ln Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6\ln Q_{t-1} + \varepsilon_t$	3.5
Log-Lin	$\ln Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6\ln Q_{t-1} + \varepsilon_t$	3.8
Lin-Log	$Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6Q_{t-1} + \varepsilon_t$	3.11
Annual/Rational Addiction		
Linear	$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_n + b_6Q_{t-1} + b_7Q_{t+1} + \varepsilon_t$	3.3
Double-Log	$\ln Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6\ln Q_{t-1} + b_7\ln Q_{t+1} + \varepsilon_t$	3.6
Log-Lin	$\ln Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6\ln Q_{t-1} + b_7\ln Q_{t+1} + \varepsilon_t$	3.9
Lin-Log	$Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6Q_{t-1} + b_7Q_{t+1} + \varepsilon_t$	3.12
Quarterly/Conventional		
Linear	$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6D_{q2} + b_7D_{q4} + b_8AD_t + \varepsilon_t$	3.13
Quarterly/Myopic Addiction		
Linear	$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6Q_{t-1} + b_7D_{q2} + b_8D_{q4} + b_9AD_t + \varepsilon_t$	3.14
Quarterly/Rational Addiction		
Linear	$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6Q_{t-1} + b_7Q_{t+1} + b_8D_{q2} + b_9D_{q4} + b_{10}AD_t + \varepsilon_t$	3.15

† Double-log and semi-log versions of Equations 3.13–3.15 have been omitted to avoid repetition.
‡ Data variables are as follows:

- Q_t = per capita consumption of cigarettes per adult in time period *t*;
- Q_{t-1} = per capita consumption of cigarettes per adult in time period *t–1*;
- Q_{t+1} = per capita consumption of cigarettes per adult in time period *t+1*;
- P_t = weighted average real retail price per cigarette in time period *t*;
- Y_t = real personal disposable income per adult in time period *t*;
- T_t = time trend variable in time period *t*;
- SR_t = index of smoking restrictions in time period *t*;
- D_m = an intercept dummy for “smoking or health” information campaign in time period *m*; 0 prior to time period *m*, 1 from time period *m* onwards;
- D_{q2} = an intercept dummy for expected seasonally depressed buying during second quarter of the year; 1 for second quarter, 0 otherwise;
- D_{q4} = an intercept dummy for expected seasonal peak buying during fourth quarter of the year; 1 for fourth quarter observations, 0 otherwise;
- AD_t = aggregate expenditure on tobacco product advertising and promotion as a proportion of all advertising expenditure in time period *t*;
- ε_t = error term.

measurement of cigarette consumption (e.g., packs of 20) and the threshold age at which persons are considered to be potential smokers (e.g., 17 years).)

Conventional Demand Model

The conventional demand model is a static model of demand, in that quantity demanded in a given period is determined by the independent variables within that period only. This model is represented as the equation:

$$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + \varepsilon_t \qquad [3.1]$$

where: Q_t = per capita consumption of cigarettes per adult in year *t*

P_t = weighted average real retail price per cigarette in year *t*

Y_t = real personal disposable income per adult in year *t*

T_t = time trend variable in year *t*

SR_t = index of smoking restrictions in year *t*

D_m = an intercept dummy for the introduction of an intensive "smoking or health" information campaign in year *m*; 0 prior to year *m*, 1 from year *m* onwards

ε_t = error term

Myopic Addiction Demand Model

Myopic means "short-sighted" and is therefore the basis for a model of short-sighted addictive behavior. It is a dynamic model of demand, in that quantity demanded in a given period is determined by the independent variables within that period, as well as by quantity demanded in the previous period—but not the future period (hence the "short-sightedness").[1] This model is represented as the equation:

$$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6Q_{t-1} + \varepsilon_t \qquad [3.2]$$

where: Q_{t-1} = per capita consumption of cigarettes per adult in year *t–1*

all other variables the same as for Equation 3.1

Rational Addiction Demand Model

This is another dynamic model of demand, in that quantity demanded in a given period is determined by the independent variables within that period, as well as by quantity demanded in

[1] The rationale underlying the myopic addiction model is covered in the discussion of the relevant independent variable, "past demand," in the context of nicotine addiction in the *Nicotine Addiction and the Role of Past and Future Demand* subsection of the **Review and Understand the Results** chapter.

the previous period and quantity demanded in the future period.[2] This model is represented as the equation:

$$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_n + b_6Q_{t-1} + b_7Q_{t+1} + \varepsilon_t \quad [3.3]$$

where: Q_{t-1} = per capita consumption of cigarettes per adult in year *t–1*

Q_{t+1} = per capita consumption of cigarettes per adult in year *t+1*

all other variables the same as for Equation 3.1

Double-Log Functional Forms

Equations 3.1–3.3 specify the conventional, myopic addiction, and rational addiction demand models, respectively, in linear functional form. Double-log functional forms of these respective models are specified as follows:

$$\ln Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + \varepsilon_t \quad [3.4]$$

$$\ln Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6\ln Q_{t-1} + \varepsilon_t \quad [3.5]$$

$$\ln Q_t = b_0 + b_1\ln P_t + b_2\ln Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6\ln Q_{t-1} + b_7\ln Q_{t+1} + \varepsilon_t \quad [3.6]$$

Semi-Log Functional Forms

Log-Lin

Log-lin functional forms of the conventional, myopic, and rational addiction demand models specified, respectively, in Equations 3.1–3.3 are expressed as follows:

$$\ln Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + \varepsilon_t \quad [3.7]$$

$$\ln Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6\ln Q_{t-1} + \varepsilon_t \quad [3.8]$$

$$\ln Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6\ln Q_{t-1} + b_7\ln Q_{t+1} + \varepsilon_t \quad [3.9]$$

The following log-lin demand specification was applied to annual aggregate time-series data from China for the period 1980–1996:

$$\ln Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + \varepsilon_t$$

where: Q_t = aggregate annual cigarette consumption in year *t*

P_t = nominal retail price per cigarette in year *t*

Y_t = nominal personal disposable income per adult in year *t*

T_t = time trend variable in year *t*

[2] The thinking underlying the rational addiction model is covered in the discussion of the relevant independent variables, "past and future demand," in the context of nicotine addiction in the *Nicotine Addiction and the Role of Past and Future Demand* subsection of the **Review and Understand the Results** chapter.

ε_t = error term

Estimated results for this model are provided in Table 3.2 in the *Administer Specification and Diagnostic Tests* section of this chapter.

Lin-Log

Lin-log functional forms of the conventional, myopic, and rational addiction demand models specified, respectively, in Equations 3.1–3.3 are expressed as follows:

$$Q_t = b_0 + b_1 lnP_t + b_2 lnY_t + b_3 T_t + b_4 SR_t + b_5 D_m + \varepsilon_t \quad [3.10]$$

$$Q_t = b_0 + b_1 lnP_t + b_2 lnY_t + b_3 T_t + b_4 SR_t + b_5 D_m + b_6 Q_{t-1} + \varepsilon_t \quad [3.11]$$

$$Q_t = b_0 + b_1 lnP_t + b_2 lnY_t + b_3 T_t + b_4 SR_t + b_5 D_m + b_6 Q_{t-1} + b_7 Q_{t+1} + \varepsilon_t \quad [3.12]$$

To simplify notation throughout the remainder of this tool, demand specifications are listed only in linear functional form, except where the discussion specifically requires the use of double-log or semi-log forms.

Demand Specifications for Quarterly Time-Series Data

An advantage of using quarterly data rather than annual data is that many more degrees of freedom are provided. Thus the demand model need not be so highly simplified.

As stated earlier, using quarterly data on tobacco product consumption based on excise tax revenue statistics can introduce an artificial seasonality into the data. There is no reason to expect retail tobacco product sales to show significant seasonal variation, except perhaps for a slight rise in aggregate cigarette consumption during festive seasons and a slight fall after the New Year—as many smokers make a resolution to try to quit. However, if the data on tobacco product consumption are based on official statistics on excise tax payments by wholesalers, an artificial seasonality is introduced by the marketing habits of tobacco product manufacturers. They typically push up sales during the final quarter of their financial year in order to meet sales targets, and allow sales to slacken during the second and/or third quarter of the financial year.

Hence the use of intercept dummy variables in Equations 3.13–3.15 to control for seasonal variation. The configuration used is based on a tobacco product manufacturing marketing cycle corresponding to calendar years.

Conventional Demand Model

The conventional demand model for quarterly data is identical to that specified for annual data (Equation 3.1), except for the addition of expenditure on advertising and promotion, and seasonal dummy variables:

Table 3.2
Results of Cochrane-Orcutt Regression on Annual Aggregate Cigarette Consumption Data for China, 1980–1996

Variable†	Coefficient	T-value	Probability Value
1. OLS Regression‡			
Intercept	3.800	60.822	0.000
Nominal cigarette price per pack (Yuan)	–0.525	–6.323	0.000
Nominal aggregate income (Yuan)	–0.002	–1.003	0.334
Time trend	0.102	13.172	0.000
F(3, 13) = 136.95; Prob. > F = 0.000; Adjusted R^2 = 0.962; DW = 2.17			
2. Cochrane-Orcutt Regression††			
Intercept	1.677	1.819	0.099
Nominal cigarette price per pack (Yuan)	–0.331	–2.399	0.037
Nominal aggregate income (Yuan)	0.007	–0.443	0.667
Lagged dependent variable	0.556	2.261	0.047
Time trend	0.047	1.594	0.124
ρ [Rho]	–0.366	–1.448	0.170
Prob. > F = 0.000; Adjusted R^2 = 0.976; h statistic = 1.25			

† Dependent variable: Logarithm of annual aggregate cigarette sales in packs per capita.
‡ Sample mean price = 1.03, therefore short-run price elasticity at sample mean = –0.54.
†† Sample mean price = 1.03, therefore short-run price elasticity at sample mean = –0.35, and long-run price elasticity = –0.66.
Source: Teh-wei Hu, Zheng Zhong Mao, "Economic Analysis of Tobacco and Opions for Tobacco Control: China Case Study" A Report Submitted to the World Bank, 2000.

$$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6D_{q2} + b_7D_{q4} + b_8AD_t + \varepsilon_t \quad [3.13]$$

where: Q_t = per capita consumption of cigarettes per adult in quarter *t*

P_t = weighted average real retail price per cigarette in quarter *t*

Y_t = real personal disposable income per adult in quarter *t*

T_t = time trend variable in quarter *t*

SR_t = index of smoking restrictions in quarter *t*

D_m = an intercept dummy for the introduction of an intensive "smoking or health" information campaign in quarter *m*; 0 prior to quarter *m*, 1 from quarter *m* onwards

D_{q2} = an intercept dummy for expected seasonally depressed buying during the second quarter of the calendar year; 1 for second quarter, 0 otherwise

D_{q4} = an intercept dummy for expected seasonal peak buying during the fourth quarter of the calendar year; 1 for fourth quarter observations, 0 otherwise

AD_t = aggregate expenditure on tobacco product advertising and promotion as a proportion of all advertising expenditure in quarter *t*

ε_t = error term

Myopic Addiction Demand Model

The specification of this model is the same as that given in the *Myopic Addiction Demand Model* subsection of the *Demand Specifications for Annual Time-Series Data* section of this chapter, except for the addition of an advertising variable and seasonal intercept dummy variables:

$$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6Q_{t-1} + b_7D_{q2} + b_8D_{q4} + b_9AD_t + \varepsilon_t \qquad [3.14]$$

where: Q_{t-1} = per capita consumption of cigarettes per adult in quarter *t–1*

all other terms the same as for Equation 3.13

Rational Addiction Demand Model

The specification of this model is the same as that given in the *Rational Addiction Demand Model* subsection of the *Demand Specifications for Annual Time-Series Data* section of this chapter, except for the addition of an advertising variable and seasonal intercept dummy variables:

$$Q_t = b_0 + b_1P_t + b_2Y_t + b_3T_t + b_4SR_t + b_5D_m + b_6Q_{t-1} + b_7Q_{t+1} + b_8D_{q2} + b_9D_{q4} + b_{10}AD_t + \varepsilon_t \qquad [3.15]$$

where: Q_{t-1} = per capita consumption of cigarettes per adult in quarter *t–1*

Q_{t+1} = per capita consumption of cigarettes per adult in quarter *t+1*

all other variables the same as for Equation 3.13

Demand Specifications for Monthly Time-Series Data

Demand specifications using monthly data are the same as for quarterly data, with these exceptions:

- Monthly rather than quarterly seasonal dummies are applied.
- It is unlikely that monthly data supports the testing of addictive models of demand. For example, Keeler *et al* (1993) find that "a one-month period of time is not long enough to measure any potential tendency towards rational addiction." Researchers must therefore either apply a conventional demand model to monthly data, and/or aggregate monthly into quarterly data.

Apply Instrumental Variable Techniques

Instrumental variable techniques can be preferable to OLS if simultaneous determination is an issue (refer to the *Determine the Identification Problem* section of the **Choose the Demand Model** chapter for further discussion). Hsieh, Hu, and Lin (1999) apply two-stage least squares (2SLS) to their Model 4 demand specification, in which price is treated as endogenous. The instruments they use are: the real cost of tobacco; the average salary cost of cigarette manufacturers; a dummy variable to control for the opening of the domestic Taiwanese cigarette market to foreign cigarettes; and the other explanatory variables in the model. They also applied 2SLS to their Model 5 specification, in which lagged demand is considered endogenous. The instruments they use are: a one-period lag of price, income, and cigarette tax; a two-period lag of price and cigarette tax; and the other explanatory variables in the model.

Treating price as endogenous produces similar results to the OLS regressions, except that the value of price elasticity of demand calculated at the sample mean changes slightly. This is shown in Table 3.3. The similarity in results suggests that the simultaneity bias is extremely small. The results for Model 5 suggest that the annual data reveal no significant addictive effect of cigarette addiction; smokers adjust their cigarette consumption completely to changes in prices and income within one year. Compare this with Van Walbeek's (2000) error-correction model (Table 3.4), which suggests that nearly two-thirds of adjustment to changes in price occur within one year.

Most departures from OLS used in analysis of tobacco product demand are variations on the theme of instrumental variables aimed at dealing with potential simultaneity bias. Consider these outstanding examples:

- Keeler *et al* (1993) conduct a sophisticated application of two-stage generalized least squares with instrumental variables to monthly per capita cigarette consumption data. The logarithm of the real (federal plus state) cigarette tax per pack is used as an instrument for real retail cigarette price per pack. Autoregressive corrections of orders AR(1) and AR(4) are used to deal with autocorrelation.
- Bardsley and Olekalns (1999) apply general methods of moments (GMM) with instrumental variables to annual data on real per capita consumption of cigarettes and other tobacco products. The rational addiction model of demand is used, and instrumental variables are necessary to deal with the endogeneity of past and future consumption. Further, three leads and lags of the real average price of cigarettes and other tobacco products are used as instruments, since the theory of rational addiction holds that optimal consumption in any period depends on the past history and expected future course of prices (see the *Nicotine Addiction and the Role of Past and Future*

Table 3.3
Regression Results for Annual Per Capita Cigarette Demand in Taiwan, 1966–1995

Independent Variable	**Model 1† (OLS)**	**Model 2† (OLS)**	**Model 3† (OLS)**	**Model 4† (2SLS)**	**Model 5† (2SLS)**
Cointegration relationship	Yes	Yes	Yes	Yes	Yes
Intercept	120.970** *2.044*	124.92*** *3.028*	116.69*** *3.359*	149.16*** *2.893*	156.68* *1.835*
Real average retail cigarette price per pack (1991 $NT)	–1.982** *–2.022* [–0.48]	–2.076** *–2.441* [–0.51]	–2.022** *–2.472* [–0.49]	–2.705** *–2.322* [–0.65]	–2.609* *–1.740* [–0.64]
Real per capita personal disposable income (1991 $NT)	0.00014 *1.314* [0.17]	0.00014* *1.706* [0.16]	0.00012** *2.457* [0.14]	0.00014* *1.713* [0.16]	0.00019 *1.600* [0.22]
Market share of low-tar brands (%)	–0.645* *–1.917*	–0.643** *–2.681*	–0.673*** *–4.009*	–0.719** *–2.758*	–0.871* *–2.251*
Dummy for strengthened warning labels from 1992 onward	–2.509 *–0.654*	–2.482 *–0.699*	—	–2.758 *–0.764*	—
Market share of imported cigarettes (%)	0.393 *1.244*	0.419 *1.604*	0.447* *1.783*	0.529* *1.775*	0.428 *1.533*
Female workforce participation rate (%)	–0.053 *–0.086*	–0.125 *–0.231*	—	–0.105 *–0.193*	—
Past consumption (number of packs)	0.251 *0.730*	0.269 *1.319*	0.303 *1.606*	0.189 *0.821*	0.009 *0.017*
AR(1)	0.047 *0.111*	—	—	—	—
Summary statistics:					
Adjusted R^2	0.91	0.91	0.92	0.91	0.91
Standard error of regression	3.17	3.05	2.96	3.10	3.14
Diagnostic tests (p values of test statistics):					
DW statistic (first-order autocorrelation)	2.01	1.95	1.96	1.93	1.63
Jarque-Bera (residual normality)	0.16	0.26	0.18	0.23	0.13
Ljung-Box Q (autocorrelation; 2 lags)	0.94	0.99	0.98	0.86	0.45
Breusch-Godfrey (autocorrelation; 2 lags)	0.87	0.99	0.98	0.96	0.49
Lagrange Multiplier ARCH (2 lags)	0.67	0.69	0.50	0.64	0.57
White (heteroscedasticity)	0.27	0.22	0.21	0.22	0.15

† Asymptotic t-statistics are italicized. Price and income elasticities calculated at sample means are listed in square brackets.
*** Significant at 1 percent level.
** Significant at 5 percent level.
* Significant at 10 percent level.
Source: Hsieh, Hu, and Lin (1999)

Table 3.4
Error Correction Model of South African Aggregate Annual Cigarette Consumption, 1970–1998

Variable	Coefficient	T-value	Probability Value
Dependent Variable: Aggregate Annual Cigarette Consumption (Millions of Packs of 20) (First Differences)			
Real aggregate personal disposable income (first differences)	0.003	3.60	0.0014
Real retail price of cigarettes (first differences)	–2.027	–5.41	0.0000
Dummy to neutralize data outlier value for 1982	197.700	4.24	0.0003
Lagged residual from cointegration equation	–0.633	–2.72	0.0119
Adjusted R^2 = 0.633; DW = 1.518			

Source: Van Walbeek (2000)

Demand subsection of the **Review and Understand the Results** chapter). GMM is used to deal with the autocorrelation associated with the leads and lags.

Administer Specification and Diagnostic Tests

As emphasized in the **Choose the Demand Model** and **Specify the Demand Function** chapters, specifying a demand model involves several choices about the functional form of the demand equation, the variables to be included, and (in the case of time-series data) the way in which the dynamic relationships between variables are modeled and analyzed. Administer specification and diagnostic tests to evaluate the appropriateness of these choices, and to determine the following round of specification choices to make when the regression analysis is repeated. The tests discussed in this section are commonly available in current econometric software packages.

Coefficient Tests

As their name implies, coefficient tests test restrictions on the estimated coefficients, including the special cases of omitted or redundant variables. They include the following:

Omitted Variables Likelihood Ratio (reference)

If a variable that should be included in the demand specification is omitted, the regression estimates are biased, in general. Further, the standard errors of the coefficients and their corresponding *t* tests are generally invalid. The omitted variables likelihood ratio test determines whether the addition of one or more variables to an existing demand specification increases the explanatory power of the model. The variables to be added must contain the same number of observations as in the original equation, and so cannot contain missing variables (as is often the case with lagged variables). This test can be applied to least squares, two-stage least squares, and binary and count models, among others.

If data are unavailable for a potentially significant variable, use a proxy for that variable rather than leave it out of the demand specification. Based on the background information on the tobacco product market, as instructed in the **Conduct Background Research** chapter, exercise judgement as to the probable relationship between the proxy and the variable it represents, and make allowance for this in the written interpretation of the regression results. (For instance, make clear that a proxy is used for a particular variable, in case policy makers incorrectly assume that the proxy variable can be used as a policy instrument for influencing demand for tobacco products.)

Redundant Variables Likelihood Ratio

If a variable is included in the demand model specification that should be left out (i.e., an irrelevant or redundant variable), the regression results are generally unbiased but inefficient. The redundant variables likelihood ratio test determines whether one or more variables from an existing demand specification have coefficients not significantly different from zero and which can therefore be excluded. This test can be applied to least squares, two-stage least squares, and binary and count models, among others.

Residual Tests

Most econometric software packages feature residual tests for autocorrelation (serial correlation), heteroscedasticity, autoregressive conditional heteroscedasticity (ARCH), and normality. Not all these tests are applicable to every form of model specification.

Testing and Correcting for Autocorrelation

Autocorrelation is usually positive. It therefore stands to reason that the most common cause of positive autocorrelation is the persistence of the influence of excluded variables. Negative autocorrelation is less common, and can be caused by the data manipulations used to change the original specification of a model into a form suitable for regression analysis (e.g., the application of distributed lag models). Hence autocorrelation can result from the omission of an important independent variable from the demand specification, or from the use of an inappropriate functional form.

Autocorrelation is more likely to be a problem when the interval between observations is short; the longer the interval, the less possibility there is for the influence of excluded variables to persist from one observation to the next. Hence, for analysis of tobacco product demand, quarterly data are likely to be less problematic than monthly data.

Due partly to the addictive nature of tobacco product consumption, the aggregate demand for tobacco products is probably stable in the short-run, and the error terms of time-series regressions is serially correlated. In addition, as explained in the *Apply Tests for Non-Stationarity and Cointegration, and Specify Error-Correction Models* section of the **Another Demand Model** chapter, time-series are often subject to non-stationarity, thus implying some form of autocorrelation.

The following are tests of first-order autocorrelation.

- The *Durbin-Watson (DW) statistic*, the most commonly applied, tests for first-order autocorrelation only. Further, this test's range of possible results includes areas of indecision, and the test is invalidated by specification of lagged dependent variables. In most applications, the Ljung-Box Q-statistic and the Breusch-Godfrey Lagrange Multiplier test are preferable.
- *Durbin's h statistic* is applied if a lagged dependent variable is included in the demand specification.

The following are tests of higher-order autocorrelation.

- The *Ljung-Box Q-statistic* tests the null hypothesis that there is no autocorrelation up to a specified order of lag. Use the Q-statistic in conjunction with graphs of residuals or graphical representations ("correlograms") of autocorrelation and partial autocorrelation processes in the residuals. Choosing which lag to use for the test is a practical challenge: too small a lag can result in autocorrelation not being detected at higher-order lags; too large a lag can give the test low power because significant autocorrelation at one lag can be blurred by insignificant autocorrelations at other lags. Therefore, repeat the test for a range of lags. This test can be applied to least squares, two-stage least squares, and non-linear least squares regression.
- The *Breusch-Godfrey Lagrange Multiplier (LM) test* is an alternative to the Q-statistic, and is applicable whether or not lagged dependent variables are specified. This test can be applied to least squares or two-stage least squares regression.

The best method for dealing with autocorrelation is to identify whether a misspecification error is responsible (such as an omitted variable), and modify the regression specification accordingly. Failing this, the adopted procedure depends on the nature of the relationship between the residuals. Most econometric software packages offer corrections for first-order autocorrelation based on linear regression techniques, such as the Cochrane-Orcutt, Prais-Winsten and Hildreth-Lu procedures (reference). These have drawbacks when working with models containing lagged dependent variables, or which feature higher-order autoregressive specifications. However, current econometric software packages also offer techniques based on non-linear regression.

An example of a Cochrane-Orcutt correction applied to annual aggregate data on cigarette consumption is detailed in Table 3.2. The results are improved, but it is also important to note how significantly the value of short-run price elasticity is altered by the procedure.

Testing and Correcting for Heteroscedasticity

Heteroscedasticity is unlikely to be a serious problem with time-series data. However, various tests for heteroscedasticity are available in econometric software packages. The preferred test is White's test, which can be applied to least squares regressions. The test is usually presented with two parameter options, namely (a) with cross terms and (b) without cross terms. The latter option is preferable if there are many independent variables in the regression.

There are several options of dealing with data if significant heteroscedasticity is found, including:

- Run the regression using the White robust standard errors option to correct the standard errors (which is likely to be the easiest and most practical option).
- Model the heteroscedasticity and use weighted least squares regression to obtain more efficient estimates.

Autoregressive Conditional Heteroscedasticity

Autoregressive Conditional Heteroscedasticity (ARCH) occurs when the size of a particular residual is related to the size of previous residuals. This occurrence does not invalidate inference from least squares results, but it does cause a loss of efficiency. Apply the ARCH Lagrange Multiplier (LM) test to least squares, two-stage least squares, and non-linear least squares regression. Current versions of most popular econometric software packages include procedures for the estimation of ARCH models.

Residual Normality

Econometric software packages often present tests of whether the regression residuals are normally distributed, such as the Jarque-Bera statistic, together with histograms (bar charts) of the distribution of the residuals. The Jarque-Bera test compares the skewness (asymmetry) and kurtosis (flatness) of the distribution of the residuals with that of the standard normal distribution. Apply the test to least squares, two-stage least squares, non-linear least squares, and binary and count models, among others, but not to cointegration regressions, whose estimates are non-normally distributed.

Specification and Stability Tests

A variety of stability tests are commonly available in popular econometric software packages, including the following:

Ramsey's Regression Specification Error Test

Ramsey's Regression Specification Error Test (RESET) is a general test for the following types of specification error:

- omitted variables
- incorrect functional form
- correlation between independent variables and the error terms caused by measurement error in the independent variables, simultaneity considerations, or the combination of a lagged dependent variable with autocorrelated error terms.

Least squares estimators are biased and inconsistent, and inference procedures are invalid, in the presence of these specification errors. If poor scores are achieved from Ramsey's RESET, carefully examine model specification and check for each of the above types of specification error by using and evaluating the following tests in combination:

1. Graph the regression residuals and check for systematic patterns.
2. Graph a Box-Cox transformation of the independent and/or dependent variables.
3. Check the value of the Durbin-Watson (D-W) or Durbin h statistic (since incorrect functional form often results in symptoms similar to those of autocorrelation). (See the subsection *Testing and Correcting for Autocorrelation* in this chapter for an explanation of these two tests.)

Chow's Breakpoint Test

Chow's breakpoint test splits a sample into two sub-samples, fits the specified equation to each of the sub-samples, and tests whether there is a significant difference between the two sets of estimates. If there is a significant difference, there is probably a structural change in the relationship(s) represented by the data sample. This is of particular relevance for annual time-series data (although a practical drawback with regard to annual data is that each sub-sample requires at least as many observations as the number of coefficients in the regression equation). Apply the test to least squares and two-stage least squares regression.

Chow's Forecast Test

Chow's forecast test splits the sample into two sub-samples, fits the regression model to the first sub-sample, and uses the estimated model to predict the values of the dependent variable in the remaining sub-sample. The smaller the difference between predicted and actual values, the greater the stability of the estimated relation over the two sub-samples. Apply the test to least squares and two-stage least squares regression.

These two Chow tests can yield conflicting results, so interpret them with care.

Multicollinearity

Analysis of demand for tobacco products is problematic due to the high number of potentially significant factors determining demand. Additionally, using aggregate time-series data is a problem because of the high degree of correlation between many of these potentially significant independent variables—particularly price, income, and advertising expenditure. Evaluate the correlation between independent variables to reveal the extent to which multicollinearity is present.

The inclusion of highly correlated variables results in multicollinearity and unstable estimates for the parameters of interest. Consequently, estimates of the impact of price and other factors on demand are sensitive to the inclusion and exclusion of other variables.

On the other hand, excluding potentially significant variables results in an omitted variables specification error, which produces biased estimates of the impact of the included independent variables. Options to deal with multicollinearity, such as imposing theoretical restrictions or using extraneous estimates, are also problematic. Though ridge regression is an increasingly popular option, it is biased at the cost of precision; and unless conducted by an experienced econometrician, ridge regression can result in seemingly precise estimates of badly biased model specifications.

Hence, there are no satisfactory practical methods for dealing with multicollinearity, and imprecise estimates may be unavoidable. If this is the case, be sure to state the implications for inference tests and interpretation of confidence intervals of the estimates obtained.

Specification and Diagnostic Test Examples

The error correction model from Van Walbeek's (2000) study of South African cigarette consumption (cited in Table 3.4) is subject to a range of common diagnostic tests, the results of which are provided in Table 3.5. Other than the Jarque-Bera test for normality in the residuals, all tests indicate that the regression equation is satisfactory on the criteria of model specification, serial correlation, and heteroscedasticity. The Chow forecast test for structural breaks is applied to each of the years 1983 to 1998, and the null hypothesis of no structural break is not rejected in any of these tests. In addition, CUSUM and CUSUM (references?) of squares tests are applied to recursive residuals, and indicate no significant evidence of coefficient instability.

Cross-Sectional Data

It is much easier to obtain aggregate time-series data than to collect individual-level cross-sectional data. On the other hand, there are also readily available cross-sectional data collected by

Table 3.5
Results of Diagnostic Tests on Error Correction Model of South African Cigarette Consumption

Test	Focus of Test	Parameters	Result	Probability Value
Breusch-Godfrey LM	Higher-order serial correlation	4 lags	$n \times R^2 = 5.1284$	0.2744
ARCH	Autoregressive conditional heteroscedasticity	2 lags	$n \times R^2 = 0.6645$	0.7173
White	Heteroscedasticity and model misspecification	No cross terms	$n \times R^2 = 2.7604$	0.9063
Jarque-Bera	Normality of residuals	N/A	$Chi^2(2) = 9.0686$	0.0107
Ramsey RESET	Model misspecification	3 fitted terms	F(3,21) = 0.0138	0.9977
Chow forecast	Structural breaks in the model	Break at 1994	F(5,19) = 1.0371	0.4246

Source: Van Walbeek (2000)

national governments and the World Bank. (See the *Choose the Variables* section in the **Build the Data Set** chapter for further discussion.) For example, researchers in Bulgaria, China, Estonia, Indonesia, Vietnam and the United States have access to household consumption surveys that include data on smoking status by individual or by household.

Analysis of cross-sectional data can be used as a substitution supplement for analysis of aggregate time-series data. However, use of cross-sectional data requires considerable care. Some of the most important reasons are:

- Information on the prices of tobacco products purchased by respondents is generally not included in household survey responses.
- In most countries, cross-sectional price data does not yield sufficient variation to allow analysis of the price-responsiveness of demand.
- It is not possible to distinguish the impacts of price and policy interventions from other underlying long-run determinants of demand for tobacco products by using cross-sectional data.
- While aggregate data cover the consumption habits of the entire country concerned, cross-sectional survey data cover a sample of the population. The results of analysis of the data are representative of tobacco product consumption habits in the country as a whole only to the extent that the survey sample is representative of the entire population.

However, cross-sectional survey data representative of the general population, or of particular target groups within the general population, can provide extremely useful supplementary evidence on critically important questions regarding tobacco product consumption, as discussed below.

Understand the Limitations of Aggregate Time-Series Data

Although cross-sectional data may not be a feasible substitute for aggregate time-series data in many low- and middle-income countries, there are limitations of using aggregate time-series data to analyze tobacco product demand.

Using aggregate data, econometric studies examine the impact of tobacco product prices and other factors only on aggregate or per capita measures of tobacco product consumption. Therefore, use aggregate data to determine the *overall* impact of a range of factors (e.g., average retail price, per capita disposable income, an index of smoking restrictions) on total demand for tobacco products. When used in conjunction with economic analysis of other issues, such as excise tax optimization (Tool 4), smuggling (Tool 7), employment impacts (Tool 5), and equity considerations (Tool 6), this is perfectly adequate for guiding the introduction and consolidation of tobacco control policy measures.

As Warner (1977: 645) points out, however, the drawback of reliance on an aggregate-based measure of demand such as per capita tobacco product consumption is that:

> *…it masks changes in the composition and individual behaviour of the smoking population: it offers no insight into variations in age, sex, income, or education distribution of smokers; it fails to distinguish a change in the number of smokers from a change in the number of cigarettes the average smoker consumes; and it ignores several other potentially important reported changes in smoking behaviour, such as reductions in the amount of each cigarette smoked and shifts from one brand to a lower "tar" and nicotine brand.*

Investigate Individual-Level Demand Decisions

Aggregate demand for tobacco products is composed of the consumption of tobacco products by many individuals. In turn, the tobacco product consumption of each of these individuals is determined by the outcomes of the following decisions they make:

1. The decision whether or not to start consuming tobacco products. This determines the *prevalence* or *participation rate* of tobacco product consumption within the population (i.e., the proportion of the total population or of particular population sub-groups who consume tobacco products).
2. The decision of how much of the tobacco product to consume daily (also known as a *conditional demand*). In

effect, this means deciding on the desired daily intake of nicotine (and tar and other harmful substances in the case of cigarettes). This issue is related to the individual's concerns about whether or not to reduce tobacco product consumption for health reasons.

3. The decision on what sub-category and brand of tobacco product to consume (e.g., plain vs. filter cigarettes, lower-tar brands vs. higher-tar brands of cigarette). The nicotine and other content of preferred sub-types and brands influence the decision regarding desired daily consumption.
4. The decision to attempt to stop consuming tobacco products, usually for health reasons but possibly also for reasons of personal finances, social disapproval, and so forth.

These decisions are approached in different ways depending on the demographic characteristics of the individual (e.g., age, gender, education level, ethnicity, community values, and income level). The nature of these processes is thus of interest to policy makers keen on extending the benefits of tobacco control to particular population sub-groups, such as youth and the poor. Individual-level data is useful for investigating issues such as the comparative price-sensitivity of various population sub-groups, especially youth and young adults. (It is of particular interest to understand how the decisions of young people to consume tobacco products are influenced, since most people begin tobacco product consumption early in life; and it is more difficult to stop the younger one starts.)

Define Key Variables

Consumption

Cigarette consumption can be defined as packs of cigarettes smoked by an individual or household on a daily, weekly, or monthly basis, depending on how the data are gathered. Usually, consumption is measured as packs of cigarettes smoked per month, or the number of cigarettes smoked per day.

However, be aware of the size of a pack of cigarettes. In some countries, pack sizes vary and may contain 10, 12, 20, or 25 individual cigarettes or "pieces" per pack. Further, in some countries sales of single cigarettes ("sticks") are common. Be sure the size of a pack is defined in a survey questionnaire. It is also useful to check the corresponding price of the reported pack to avoid miscoded information. For example, a questionnaire may ask about packs of *kreteks* or cigarettes consumed, but the individual may report single *kreteks* or cigarettes and give the corresponding, single-item price.

Price

Problem of Determining the Price Variable

Finding a meaningful and statistically acceptable price variable in cross-sectional survey data is a major challenge. Most surveys do not ask for the price of a pack of cigarettes paid by the respondent. If they do report price information, only smokers respond with this information in two possible forms: total paid expenditures on their cigarette consumption or the price per pack of their chosen brand. Estimate average price per pack by dividing total expenditure by the number of packs of cigarettes consumed, and check this against independent information on the actual prices. This estimated price variable is endogenous, since the denominator of this independent variable is created from the dependent variable (i.e., quantity of cigarettes consumed).

Importance of the Price Variable

Price (of which tax usually comprises a large part) influences smoking behavior. An increase in price affects a smoker's decision about the number of cigarettes to smoke, whether to switch to cheaper brands, or to quit smoking altogether. Price also affects the non-smoker's decision of whether or not to start smoking.

To understand how price influences smoking decisions, it's necessary to estimate the price elasticity of cigarettes. The price elasticity measures individuals' sensitivity to price changes. The price elasticity of demand for cigarettes has very strong policy implications. Once the price elasticity is known, one can determine how much to increase price in order to achieve a planned reduction in consumption, and what will be the increase in government revenue as a result of the price (tax) increase.

Problem of Using Price Variable in Cross-Sectional Data

Surveys collect self-reported cigarette prices from respondents who smoke. As a result, the price variable in the data can reflect endogenous choices of cigarette brands and quality. In other words, individuals exercise some choice over the price they pay for cigarettes, rather than the price they pay being determined exogenously, or entirely independently of their decisions about whether and how much to smoke. So the price variable can be correlated with unobservable differences in preferences, yielding biased estimates of the price elasticity. Because of this possibility, the price variable may be endogenous.

Price Value Unassigned for Non-Smokers

Whether or not they smoke, individuals face a price value for cigarettes. That is, price plays a significant role in deciding whether or not to smoke—for smokers and non-smokers. In a regression, if no other price is assigned for non-smokers so that the price variable has the value zero for non-smokers, the price elasticity estimate can be positive because of the weight of the zero value in the price distribution from all the non-smokers.

Assign a Price Variable Value

There are two major problems for finding the price variable in a cross-sectional survey: zero price for non-smokers and endogeneity of price variable. There are two approaches to resolving these problems. The first is to find published average cigarette price data collected by the government or cigarette industry in various locations, such as cities, counties, and provinces across the country. Based on the individual respondent's location, the price of cigarettes can be collated to each respondent, regardless of whether the respondent is a smoker or non-smoker. This approach assumes that there is enough of a price variation across the country due to differences in local tax rates, transportation costs, income differences, and cost of living differences. On the other hand, this is a desirable approach, because it assumes that the individual consumer is a price taker and faces a market price. No endogeneity problem exists in this approach. Also, regardless of whether the individual is a smoker or non-smoker, there is a market price for cigarettes. Studies carried out by Wasserman and Hu provide examples of this approach.

The second approach is to assign a price variable value for non-smokers by estimating a regression with price as the dependent variable, and the independent variables are the individual's characteristics—such as gender, income, and education—that are associated with smoking behavior. It is possible to use this regression to assign a predicted price for non-smokers with specific characteristics, based on the price paid by smokers with matched characteristics (living in the same neighborhood, with similar income, same age, sex, education, occupation, family structure, etc).

Define Other Variables to Capture the Characteristics of Households and Individuals

Age

If a survey asks respondents of their age, then create age category (dummy) variables. Define age groups based upon perceived smoking habit, census clarification, availability of information, and number of observation in the data set. For instance, a series of groups ranging in age from 16–25, 26–40, 41–55, and so on might be feasible. In other situations, only two age groups—adults aged 19 and younger and those of age 20 and over—might be preferable.

Assign each person a value of 1 for the categorized age group into which they fit, and 0 for all other age groups. Omit one of the age group variables from the regression as the referenced age group, and interpret all the other coefficients compared to the referenced group.

Gender

It is common to assign a value of 1 for one gender group and a value of zero for a reference group. Define the gender variable as 1 for male and 0 for female. Since 1 is given for male, the coefficient of the gender represents males and should be interpreted by referencing females.

Education

The education variable can be defined in several different ways: educated versus not educated, high school and above education versus less than high school education, or several education variables such as primary, secondary, high school, technical, and so on—in which case the non-educated group is provided as a reference. The education variable can have a high correlation with the income variable, creating multicollinearity. That is, as an individual's education level increases, income is more likely to increase as well. But education can also play a negative role in a smoking decision. Since more educated individuals are likely to expose the adverse health impacts of cigarette smoking, they may therefore reduce their consumption, even though their income increases.

Religion

Some religions outlaw smoking and require followers not to smoke. This is the case in the United States among Mormons, and in Egypt among Muslims. In countries where people have several different religious beliefs, it is necessary to create a religion variable similar to the age and gender variables.

Tobacco Control Variables

If tobacco control policies do not differ between states or provinces and the data is available only at one point of time, then there is no variation to include a variable for tobacco control policies in the estimation. But if a country has, for example, two years of data collected before and after major tobacco control policies take place, it is useful to compare the pre- and post-policy impact on cigarette consumption. In this case, merge two data sets and measure the impact by creating a discrete variable. For example, if the first survey is conducted in 1996, assign those observations the value of 0, and assign the later survey observations—assuming they are taken in 1999—the value of 1.

The caveat for this definition is that the variable can capture the impact of other developments taking place simultaneously with tobacco control policies. To avoid a dichotomous tobacco control variable from capturing other factors, one solution is to control provinces and regions in the estimation, depending on the availability of information and the number of observations.

If provinces or states implement different tobacco control policies, try to create a tobacco control variable. For example, if tobacco use is restricted only in public places, assign the variable a value of 1; if restricted all public and health places, assign the variable a value of 2; if restricted all public places, health institutions, and schools, assign the variable a value of 3; if smoking is restricted everywhere and some restrictions are brought for advertising in print and electronic media, assign the variable a value of 4; and so on. This definition works well when the time series data is more than two years. It is also possible to create different tobacco control variables based on the strength of tobacco control policies applied in different provinces or states.

The Identification Problem

Endogeneous Price Variable

If price endogeneity is in fact a problem, there are two types of estimation models for household or individual level data that take it into account: two-stage least squares (2SLS) estimation with an instrumental variable (IV), and the two-part model developed by Cragg (1971).

An alternative to applying either of these models is to replace the price variable with a cigarette tax variable. This allows for the estimation of tax elasticity, which can then be converted to price elasticity.

Find the Correct Instrumental Variable

An instrumental variable to replace an endogenous price variable serves the same purpose as the price variable in affecting consumption behavior, but it must be exogenous, or entirely independent of the individual's decision about how much to smoke. The most suitable replacement instrumental variable is tax per pack. Use tax per pack in a demand equation to develop an estimate of tax elasticity, then convert tax elasticity to price elasticity, as follows:

Assume the following linear demand model (due to endogeneity of cigarette prices, use a tax variable instead of a price variable):

Consumption = $\alpha + \beta$ Tax + μ

Estimate the price elasticity of demand for cigarettes with this specification by:

$$\left[\left(\bar{\rho}/\bar{q}\right)\beta\right]/\left(\partial\rho/\partial t\right)$$

where: β = the estimated coefficient of tax variable in the regression equation above

$\bar{\rho}$ = the sample mean of the cigarette price

$\bar{q}$ = the sample mean of per capita cigarette consumption

$\partial p/\partial t$ = the change in cigarette prices resulting from a change in excise taxes. This can be estimated by regressing price as a function of tax:

Price = $\alpha + \gamma$ Tax + μ

and the estimated coefficient of tax (γ) is $\partial p/\partial t$.

Use Tax as an Instrumental Variable

In order to estimate a demand equation, it is necessary to have a price/tax variable with many values, not just a single value for all consumers at the time of the survey. (If price/tax has only one single value for all observations, then one can only estimate a single point and not a whole demand curve.) Cigarette demand studies typically get variations in price due to tax differences over time and/or across different tax jurisdictions (e.g., the 50 U.S. states all have different cigarette taxes, so even if a national survey is limited to a single year, it has considerable tax variation). However, in most developing countries household or individual surveys are cross-sectional at one point in time, with no local or provincial taxes. Further, one or two years of household data do not provide enough variation in price/taxes to include tax as a variable in the analysis.

Although tax rates may not vary by provinces or states in most countries, cigarettes are often taxed at different rates based on length, production size, quality, type, manufacture process (hand-made vs. machine-made), and origin. When the characteristics of cigarettes that individuals smoke are identified from the survey—even one done at a single point in time—there may be enough tax variation. On the other hand, if there is no characteristic information other than price, then it is necessary to find other sources showing detailed price information by type, size, quality, origin, and so on. This information can be obtained from commerce departments and/or customs and tax administration departments of the Ministry of Finance.

With this data, use price to determine the types of cigarettes smoked and assign a corresponding tax level. However, be careful about price variations of each brand of cigarettes in urban and rural areas, in different provinces or states, or even in different kinds of sales points (e.g., supermarkets, street vendors, convenience stores, and gas stores).

There is no rule of thumb about how much variation is needed in a variable to get a reasonable estimate. But where taxes vary depending on several different characteristics, as mentioned above, there is usually enough variation in the tax variable to get a reasonably good estimate.

Specify Demand Functions for Cross-Sectional Data

Use data from household consumption surveys that include information on smoking status by individual or by household to estimate demand elasticities using a two-part demand model, as follows:

1. Use probit or logit methods to estimate a smoking participation equation.
2. Use least squares methods to estimate average daily cigarette consumption by smokers, with the logarithm of the average daily consumption variable as the dependent variable.

The independent variables are the same in both equations of the model. Express the second part as follows:

$$\ln Q_{jl} = c_0 + c_1 P_l + c_2 Y_{jl} + c_3 V_{jl} + c_4 F_{jl} + c_5 SR_l + \varepsilon_t$$

where: $\ln Q_{jl}$ = logarithm of average daily consumption of cigarettes by the *j*th individual in the *l*th locality

P_l = real average price of cigarettes per pack in the *l*th locality

Y_{jl} = real disposable personal income of the *j*th individual in the *l*th locality

V_{jl} = a vector of individual demographic characteristics such as age, gender, ethnic group, education level, marital status, and religious observance

F_{jl} = a vector of family characteristics including family size, identity of household head (father or mother), and education level of household head

SR_l = index of smoking restrictions in the *l*th location

ε_t = error term

Demand Models for Household or Individual Level Data

There are several demand models to use for analysis of individual-level data. This section provides the specific steps and calculations necessary to conduct two-stage least squares estimation and the two-part model.

Two-Stage Least Squares Estimation

The two-stage least squares estimation, as its name implies, requires two stages because the price variable is endogenous and, therefore, must be resolved. The first stage is to predict the price variable. First, find an independent variable that directly affects price but does not directly affect consumption. When the price is predicted, it is not endogenous anymore. Then use the predicted price variable as an explanatory or independent variable in the second step estimation of the demand model.

The model takes the following formula:

Step A1:

$$price = \delta_0 + \delta_1 tax + others$$
$$\Rightarrow \textit{from here, obtain the " predicted price"}$$

Step A2: $$consumption = \psi_0 + \psi_1 \, predicted\ price + others$$

Estimate the price elasticity from this formula, as such:

$$\text{price elasticity} = \frac{\partial consumption}{\partial predicted\ price} \times \frac{mean\ predicted\ price}{mean\ consumption}$$

$$= \psi_1 \times \frac{mean\ predicted\ price}{mean\ consumption}$$

To estimate tax elasticity from the model, conduct the following:

$$\text{tax elasticity} = \frac{\partial consumption}{\partial tax} \times \frac{mean\ tax}{mean\ consumption}$$

$$= \frac{\partial consumption}{\partial price} \times \frac{\partial price}{\partial tax} \frac{mean\,tax}{mean\,consumption}$$

$$= \psi_1 \times \delta_1 \times \frac{mean\,tax}{mean\,consumption}$$

However, if logs are involved, estimate the price and tax elasticity differently. For example, suppose:

Step B1: $\log(price) = \alpha_0 + \alpha_1 \log(tax) + others$
$\Rightarrow$ *from here, obtain the "predicted* $\log(price)$"

Step B2: $consumption = \beta_0 + \beta_1 \, predicted \log(price) + others$

Then

price elasticity = $\dfrac{\beta_1}{mean\,consumption}$

And

tax elasticity = $\dfrac{\partial consumption}{\partial tax} \times \dfrac{mean\,tax}{mean\,consumption}$

$$= \frac{\partial consumption}{\partial \log(price)} \times \frac{\partial \log(price)}{\partial tax} \frac{mean\,tax}{mean\,consumption}$$

$$= \beta_1 \times \frac{\alpha_1}{mean\,tax} \times \frac{mean\,tax}{mean\,consumption}$$

$$= \beta_1 \times \alpha_1 \times \frac{1}{mean\,consumption}$$

In both equations the log dependent variable of log (consumption) variable is not used because, for non-smokers, the consumption variable is zero. Since the *log of zero is not defined*, the observations for non-smokers are dropped from the estimation if log (consumption) is used.

Two-Part Model Estimation

Craig (1971) developed two-part model estimation in 1971 to avoid the problems found in typical logarithmic regression models in which the dependent variable can assume a value of zero for non-smokers. This model has two parts, each involving a regression. The first regression estimates an individual's decision to smoke (or having a smoker in a household) as a function of the same variables used in the demand model by using the entire sample. As this is a probability model (probit or logit), the dependent variable is a dichotomous variable equal to 1 for smokers and 0 for non-smokers, or 1 for households with smokers, 0 for households without smokers. The second regression uses ordinary least square techniques (OLS) on only part of the sample—smokers or households with smokers—to estimate the demand for cigarettes.

Choose Probit or Logit at the First Step

Estimate the price elasticity of decision to become a smoker from the first step estimation of probit and logit models. Since the second step estimation uses the OLS technique, the price elasticity of cigarette demand estimation depends on which model (e.g., linear, log linear, double log linear) is used.

Why Probit or Logit?

Probit and logit models estimate the probability of being a smoker for individual level data (or having a smoker in a household for household level data), and measure this likelihood after controlling the relevant variables used in the demand model. The dependent variable in the first step is defined as a dichotomous variable with the values 1 for smokers, and 0 for non-smokers.

Apply this to the aforementioned formula to produce:

$$\Pr(y=1) = f\left(x's \; and \; \beta's\right)$$

where: x′s = variables

β′s = the variables' coefficients

In practice, the probability function is rarely a linear form, since the linear probability model allows for predicted values to be outside of the range (0,1). Instead, the probability function is usually either the standard normal density, or the logistic distribution, both of which provide predicted values within the range (0,1). If the former is used, the result is a probit model. If the latter is used, the result is a logit model.

The Probit Model

Estimate price elasticity of decision to smoke from the first step. The probit model appears in Equation 3.16 by using the first two specifications for the distribution of being a smoker or y = 1.

$$\Pr(y=1) = \Phi(\beta'x) = \int_{-\infty}^{\beta'x} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}z^2\right) dz$$

$$\Pr(y=0) = 1 - \Phi(\beta'x)$$

$$E(y|x) = 0 \times \left(1 - \Phi(\beta'x)\right) + 1 \times \Phi(\beta'x) = \Phi(\beta'x) \qquad [3.16]$$

where: x = k × 1 vector of independent variables

β = k × 1 vector of coefficients corresponding to the independent variables

Φ = the standard normal cumulative distribution function

Use the last equation to calculate the average change in E(y|x) with respect to the k^{th} (price) variable:

$$\frac{\partial E(y|x)}{\partial x_k} = \frac{\beta_k}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(\beta'x)^2\right)$$

Note that in the probit model, the derivative of E(y|x) with respect to x_k varies with the level of x_k and the other variables in the model. Therefore, evaluate the derivatives *at the mean values* of all the x-variables in the sample. Then, determine the elasticity (at the means) of E(y|x) with respect to the kth variable with the following formula:

$$\frac{\partial \mathrm{E}(y|x)}{\partial x_k}\frac{\overline{x_k}}{\mathrm{E}(y|x)}=\frac{\beta_k}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\beta'\bar{x}\right)^2\right)\frac{\overline{x_k}}{\mathrm{E}(y|x)}$$

where: β_k = the coefficient on the kth (price) variable

E(y|x) = the average value of the y-variable

For example, suppose y_i assumes value 1 if person i is a smoker, and the value 0 if person i is a non-smoker. Then, E(y|x) is the percentage of smokers in the sample, $\overline{x_k}$ is the average value of the kth (price), and $\beta'\bar{x}$ is equal to:

$$\beta_0\overline{x_0}+\beta_1\overline{x_1}+\beta_1\overline{x_2}+\ldots\beta_k\overline{x_k}$$

where the "bars" represent sample averages (or mode) of the underlying variables such as income, household size, age, sex, and so on.

The Logit Model

The logit model appears in the third regression below, by using the first two specifications for the distribution of y.

$$\Pr(y=1)=\Lambda(\beta'x)=\frac{\exp(\beta'x)}{1+\exp(\beta'x)}$$

$$\Pr(y=0)=1-\Lambda(\beta'x)$$

$$\mathrm{E}(y|x)=0\times(1-\Lambda(\beta'x))+1\times\Lambda(\beta'x)=\Lambda(\beta'x)$$

where: x = the vector of independent variables

β = the vector of coefficients corresponding to the independent variables

Λ = the logistic distribution function

Calculate the average change in E(y|x) with respect to the kth variable as:

$$\frac{\partial \mathrm{E}(y|x)}{\partial x_k}=\beta_k\frac{\exp(\beta'x)}{(1+\exp(\beta'x))^2}=\beta_k\Lambda(\beta'x)(1-\Lambda(\beta'x))$$
$$=\beta_k\mathrm{E}(y|x)(1-\mathrm{E}(y|x))$$

Evaluate the derivative *at the mean values* of x-variables in the sample. Determine the elasticity (at the means) of E(y|x) with respect to the kth variable with the usual formula:

$$\frac{\partial \mathrm{E}(y|x)}{\partial x_k}\frac{\overline{x_k}}{\mathrm{E}(y|x)}=\beta_k\mathrm{E}(y|x)(1-\mathrm{E}(y|x))\frac{\overline{x_k}}{\mathrm{E}(y|x)}\beta_k\overline{x_k}(1-\mathrm{E}(y|x))$$

where: E(y|x) = the average value of the y-variable

For example, suppose y_i takes on value 1 if person i is a smoker, and the value 0 if person i is a non-smoker. Then, E(y|x) is the percentage of smokers in the sample, $\overline{x_k}$ is the average value of the k^{th} variable, and β_k is the coefficient on the k^{th} variable in the regression model.

Estimate total price elasticity from the two-part model specified above. In the two-part model, in order to estimate overall price elasticity, first estimate probability of decision to smoke from the first step estimation as explained above for both probit and logit specification. Then estimate price elasticity of cigarette consumption conditional on being a smoker by using one of the OLS estimation techniques. Then determine the overall price elasticity by summing together the price elasticity of participation (from the first regression) and the price elasticity of consumption (from the second regression).

Expect Results for Quantitative Independent Variables

Remember that individual-level survey data on tobacco product consumption is compiled from respondents' own statements regarding their average daily intake. Comparisons of self-reported consumption data with aggregate sales data consistently suggest that self-reported consumption surveys significantly understate actual tobacco product sales. Studies using individual-level survey data generally assume that underreporting is proportional to true consumption across particular target groups (e.g., specific age, gender, or socioeconomic groups).

Price

There are likely to be several difficulties associated with the use of the price variable in cross-sectional demand analyses in most countries:

- Data on the prices paid for tobacco products is often not gathered in household surveys. Nevertheless, after some investigation, average prices for tobacco products prevailing in particular locations can usually be collated with the data entries of particular respondents.
- Another way of dealing with lack of survey data on tobacco product prices is to calculate average prices from survey responses on expenditures and tobacco consumption. One drawback to this approach is that self-reported underestimation of tobacco product consumption can result in systematic overestimation of average prices. Another problem is that this method makes price endogenous (which is not otherwise a problem with individual-level data), but instrumental variable techniques can deal with this difficulty.
- In any case, most countries do not experience significant variation in tobacco product prices between localities. In

these circumstances, price is unlikely to be a statistically significant variable—in contrast to the results of demand analysis of aggregate time-series data. It is important to carefully explain to intended target audiences the reasons for these apparently contradictory results, in order to prevent confusion and avoid conveying the impression that price does not have an impact on tobacco product consumption.

Income

Cross-sectional data from individual or household surveys are likely to have wider variation in the income variable than aggregate time-series data, so the income variable is probably more statistically significant than in time-series studies.

Advertising and Promotional Activity

There are many difficulties in analyzing the impact of tobacco industry advertising on tobacco product consumption (see the *Expect Results for Quantitative Independent Variables* section of the **Review and Understand the Results** chapter for a comprehensive discussion). Keep these difficulties in mind when analyzing cross-sectional survey data as well.

Interestingly, the only study on the impact of cigarette advertising in the United States using individual-level cross-sectional data and appropriate measures of advertising exposure (Lewit, Coate, and Grossman, 1981) finds evidence that televised cigarette advertisements significantly increase youth smoking.

Expect Results for Qualitative Independent Variables

Health Information and “Counter-Advertising”

As with tobacco industry advertising, the impact of health information and “counter-advertising” campaigns is difficult to model, even in the best of times. Further, analysis of cross-sectional data is difficult because the impact of anti-smoking campaigns can be significantly overstated due to widespread under-reporting of tobacco product consumption by survey respondents. As with tobacco product advertising, therefore, it is necessary to exercise particular care in the interpretation of results on health information variables.

Smoking Restrictions

Econometric analysis in the United States tends to find that workplace smoking restrictions both lower the daily cigarette consumption rate of current smokers, and are associated with lower incidence of smoking initiation among non-smokers. Nonetheless, it is important to keep in mind the potential simultaneity between low smoking participation rates and smoking restrictions, and to apply appropriate methods to correct for this.

Youth Access Limitations

In 1997, over 40 countries banned the sale of cigarettes to minors, typically by establishing a minimum legal purchase age for cigarettes and restricting the distribution of free samples to underage youth. However, a few recent econometric analyses examine the impact of such limits on youth access in the United States, and generally find little or no impact on youths' consumption of cigarettes and other tobacco products. This lack of impact is attributed to the relatively weak enforcement of youth access restrictions. Further research in the United States finds that (need reference), when limits on youth access are comprehensively and aggressively enforced and therefore highly complied with, the prevalence of youth smoking is significantly reduced.

Keep in mind that, within those low- and middle-income countries that have legislated youth access limitations, a dummy variable to control for the impact of such restrictions is highly unlikely to have a significant influence if the restrictions are not effectively enforced. Hence, be sure to specify the extent of enforcement as an intercept dummy in conjunction with the dummy on access restrictions.

Demographic Factors

The demographic structure (e.g., age, education level, ethnicity, and community values) of a population can be important in explaining tobacco product consumption. For example, Bardsley and Olekalns (1999) point out the importance that a declining number of older Australian smokers—who became addicted to nicotine during their military service in World War II—has on tobacco product consumption.

The influence of demographic factors is summarized as follows:

Age

It is popularly suggested that youth are more price-responsive than adults (Chaloupka and Warner, 1999), at least in the short run, for the following reasons:

- Due to the addictive nature of smoking, long-term adult smokers are less likely to adjust quickly to changes in price than young smokers (who have been smoking for a relatively short time) or young prospective smokers (who are considering smoking or in the early stages of experimentation).
- Peer influence is likely to be more significant among youth than among adults.
- The proportion of disposable income a youth spends on tobacco products is likely to be much higher than that of an adult smoker.
- Youth tend to have a much shorter time horizon (i.e., be more oriented towards the present) than adults.

The econometric evidence on the relationship between age and price-sensitivity of demand for tobacco products is mixed. Early studies in the United States conclude that overall cigarette demand by youth was up to three times as price-responsive as that of adults, while later studies find no significant differences in price responsiveness by age. The most recent U.S. studies (Chaloupka and Wechsler, 1997), based on much larger samples and more careful econometric specification, confirm the idea that youth and young adults are more responsive to cigarette price than older adults. Evidence also shows that, in the United States, there is an inverse relationship between the price elasticity of demand for smokeless tobacco products and age.

Because of the lack of cross-sectional price variation in many low- and middle-income countries, perhaps it is possible that the only way to test these propositions about the relative price-responsiveness of youth tobacco product consumption is with panel or longitudinal data.

Gender

Several studies (reference) in the United States find that men are less price-sensitive than women. In addition, an early application of the Becker and Murphy (1988) model of rational addiction to individual-level survey data finds that U.S. men behave more myopically and are relatively responsive to price than women.

Race/Ethnicity

Studies in the United States find that cigarette demand among African Americans and Hispanics is more price-sensitive than among white non-Hispanics. Similar differences are observed among black and white youth in the United States. However, expect collinearity between race and income in certain multi-cultural societies. For example, high correlation between socioeconomic status and race/ethnicity in the United States means that explanatory variables controlling for race probably reflect the influence of income on demand for tobacco products, and *vice versa*.

Education Level

Cigarette demand among U.S. youth is relatively less elastic for more educated or higher-income individuals. Similarly, in applying the Becker and Murphy (1988) model of rational addiction to U.S. individual-level survey data, it is found that less educated persons behave more myopically than their more educated counterparts. In addition, less-educated persons are more price-responsive than higher-educated persons.

Community Values and Religion

Certain religious denominations frown on the consumption of tobacco products. Be aware of this and other community values when modeling tobacco consumption. (Refer to the **Conduct Background Research** chapter for more information on the importance of community values and religion.)

Pooled Time-Series and Cross-Sectional Data

Few researchers in low- or middle-income countries enjoy the luxury of access to sizeable panel or longitudinal data sets. Those that do, however, can take advantage of time-series of individual-level cross-sectional data to address more detailed questions about the determination of tobacco product demand than single-period cross-sectional data, including the following:

- How much of the reduction in cigarette consumption resulting from retail price increases or other interventions is due to quitting among existing smokers, as opposed to cutting back daily consumption by the same group or deterring prospective new smokers from starting?
- To what extent does increased health information result in reductions in the daily consumption of cigarettes by smokers, rather than in shifts to brands with lower "tar" and nicotine content?

A shortcoming of cross-sectional data in many countries is the lack of price variation between localities (see the *Cross-Sectional Data* subsection of this chapter). The availability of time-series of cross-sectional data removes this difficulty. Also, while time-series data sets and cross-sectional data sets can each have only a few observations, pooling time-series of cross-sectional data often provides a sample large enough for meaningful regression analysis.

The basic methodological and technical issues of time-series data, as discussed in this tool, are also applicable to pooled time-series of cross-sectional data. The simplest model is to introduce both time-dummy variables and cross-section dummy variables, the so-called "fixed effect model." However, most econometric software packages now include a range of sophisticated options for estimating equations on pooled data. These include the use of "pools" and "systems" to estimate general or more complex models using two-stage least squares or non-linear specifications, and the ability to estimate models with error-component methods. Hence analysis of pooled data is likely to be more complex than using time-series or cross-sectional data, but also more rewarding.

VII. Review and Understand the Results

Calculate Elasticities of Demand

This section explains the calculation of elasticities of demand for conventional and addictive demand models in double-log, linear, log-lin, and lin-log functional forms, using price elasticities as an example. The details are summarized in Table 3.6. The notation used follows the specifications of demand functions detailed in the **Specifying the Demand Function** chapter.

Conventional Demand Model

In the conventional demand model, calculate the price elasticity of demand according to the following forms.

Double-Log Functional Form

If the demand function is specified in double-log (log-linear, log-log) functional form, short-run price elasticity of demand is simply the estimated coefficient on the price independent variable. The double-log functional form implies constant elasticities, so this value is assumed constant over the range of the data series.

Linear Functional Form

If the demand function is specified in linear functional form, short-run price elasticity of demand at time *t* is calculated as follows:

$$e_{Pt} = b_1 \times P_t / Q_t \qquad [3.17]$$

where: e_{Pt} = price elasticity of demand at time t

Q_t = quantity demanded in period t

P_t = price in period t

Table 3.6
Calculation and Characteristics of Elasticities of Demand for Time-Series Data, by Type of Demand Model, Data Term, and Functional Form

	Functional Form			
Model/Regression/ Term	**Double-Log (Constant Elasticity)**	**Linear (Variable Elasticity)**	**Log-Lin (Variable Elasticity)**	**Lin-Log (Variable Elasticity)**
Conventional				
short-run	b_i	$b_i \times X_t / Q_t$	$b_i \times X_t$	$b_i \times (1 / Q_t)$
Conventional (Long-Run Cointegration)				
long-run	b_i	$b_i \times X_t / Q_t$	$b_i \times X_t$	$b_i \times (1 / Q_t)$
Conventional (ECM Cointegration)				
short-run	b_i	$b_i \times X_t / Q_t$	$b_i \times X_t$	$b_i \times (1 / Q_t)$
Addictive				
short-run	b_i	$b_i \times X_t / Q_t$	$b_i \times X_t$	$b_i \times (1 / Q_t)$
long-run	b_i / k	$b_i \times X_t / Q_t \times k$	$b_i \times X_t / k$	$b_i \times (1 / k \times Q_t)$

b_i = estimation coefficient on relevant independent variable (e.g., price, income)
X_t = value of independent variable at time *t*
Q_t = value of dependent variable (quantity demanded) at time *t*
k = partial adjustment factor = (1 – estimated coefficient on lagged dependent variable)

Log-Lin Functional Form

If the demand function is specified in log-lin functional form, short-run price elasticity of demand at time *t* is calculated as follows:

$$e_{Pt} = b_1 \times P_t \qquad [3.18]$$

where: e_{Pt} = price elasticity of demand at time *t*

P_t = price in period *t*

Lin-Log Functional Form

If the demand function is specified in lin-log functional form, short-run price elasticity of demand at time *t* is calculated as follows:

$$e_{Pt} = b_1 \times (1 / Q_t) \qquad [3.19]$$

where: e_{Pt} = price elasticity of demand at time *t*

Q_t = quantity demanded in period *t*

Note that when applying linear and semi-log functional forms, price elasticity is normally calculated at the mean values of P_t

and/or Q_t. It is not be sensible to calculate it at extreme values of P_t and/or Q_t if they vary greatly from the mean values.[3]

Short-run elasticities of demand for other independent variables (e.g., income) are calculated in the same manner.

Addictive Demand Models

Addictive models of demand are dynamic, implying a partial adjustment process within each time period. Consider the partial adjustment model:

$$Q_t = Q_{t-1} + k\,(Q^*_t - Q_{t-1}) \qquad [3.20]$$

where: Q^*_t = the desired level of consumption

k = the proportion of the adjustment from past consumption towards the desired level of consumption which takes place during period *t*, such that $0 \leq k \leq 1$

If one assumes a simplified demand model based on Equation 3.2 such that:

$$Q^*_t = b_1P_t + \varepsilon_t \qquad [3.21]$$

and rearranges Equation 3.20 accordingly, the demand function to be estimated becomes:

$$Q_t = kb_1P_t + (1 - k)Q_{t-1} + k\varepsilon_t \qquad [3.22]$$

Hence, calculate the price elasticity of demand[4] according to the following forms.

Double-Log Functional Form

If the demand function is specified in double-log (log-linear, log-log) functional form, short-run price elasticity of demand is simply the estimated coefficient on the price independent variable. As the double-log functional form implies, this value is constant. Long-run price elasticity of demand (also constant) is the estimated coefficient on the price variable divided by k ($= 1 - b_6$).

Linear Functional Form

If the demand function is specified in linear functional form, short-run price elasticity of demand at time *t* is calculated using Equation 3.17.

Long-run price elasticity of demand at time *t* is calculated as follows:

$$e_{Pt} = b_1 \times P_t / (1 - b_6)Q_t \qquad [3.23]$$

where variables are the same as for Equation 3.17, and b_6 is the coefficient on Q_{t-1} estimated from Equation 3.2.

[3] Refer to Table 3.3 for examples of price and income elasticities of demand calculated from data on annual per capita cigarette demand in Taiwan.
[4] Derived from Equation 3.2.

Log-Lin Functional Form

If the demand function is specified in log-lin functional form, short-run price elasticity of demand at time *t* is calculated using Equation 3.18.

Long-run price elasticity of demand at time *t* is calculated as follows:

$$e_{Pt} = b_1 \times P_t / (1 - b_6) \qquad [3.24]$$

where variables are the same as for Equation 3.18, and b_6 is the coefficient on Q_{t-1} estimated from Equation 3.2.

Lin-Log Functional Form

If the demand function is specified in lin-log functional form, short-run price elasticity of demand at time *t* is calculated using Equation 3.19.

Long-run price elasticity of demand at time *t* is calculated as follows:

$$e_{Pt} = b_1 \times (1 / (1 - b_6)\ Q_t) \qquad [3.25]$$

where variables are the same as for Equation 3.19, and b_6 is the coefficient on Q_{t-1} estimated from Equation 3.2.

Elasticities of demand for other independent variables (e.g., income) are calculated in the same manner.

Use of Cointegration Regression

When cointegration regression methods[5] are used, calculate the short-run and long-run elasticities for particular years by using the corresponding *fitted values* of P_t and/or Q_t from the long-run cointegration equation, rather than the *actual data values* of P_t and/or Q_t. This ensures that the elasticities are based on equilibrium (long-run) rather than disequilibrium (short-run) conditions, providing a sounder basis for analysis of movements in demand over time.

Expect Results for Quantitative Independent Variables

This section briefly outlines the expected estimation results for each of the independent variables of the demand specifications described above. The results of prior research are investigated and used to determine the influence each factor is likely to have on demand for tobacco products.

[5] See the *Apply Tests for Non-Stationarity and Cointegration, and Specify Error-Correction Models* section of the **Another Demand Model** chapter.

Price

The literature on price-demand focuses on how price changes influence both the decisions of whether or not to smoke and how many cigarettes to smoke (given that one chooses to smoke). The responsiveness of demand to price changes is measured by the price elasticity of demand, which is defined as the percentage change in demand resulting from a one percent change in price. Economic theory predicts that demand and price changes move in opposite directions (i.e., if price rises, demand falls), so the numerical measure of price elasticity of demand is expected to be negative. For example, a –0.5 value for price elasticity of demand means that a 1 percent rise in price results in a 0.5 percent decline in demand.

Most recent conventional models of cigarette demand estimate price elasticities of consumption ranging from –0.14 to –1.23, but most results from developed countries fall within the narrower range –0.3 to –0.5. Although there are numerous studies of the price-demand relationship in industrialized countries, studies on developing countries have occurred only in the last ten years. A small but growing number of studies examine the demands for cigarettes and other tobacco products in a few low- and middle-income countries, while new research is beginning to focus on others.

Arguably, economic theory suggests that demand in low- and middle-income countries is more responsive to price—due to relatively low incomes—than demand in wealthier countries. In general, the findings from econometric studies support this hypothesis, suggesting that cigarette demand in lower-income countries is at least twice as sensitive to price as demand in higher-income countries.

Evidence on own-price elasticity of demand from low- and middle-income countries includes the following estimates:

- *Papua New Guinea*: Chapman and Richardson (1990) are the first to empirically estimate the impact of tobacco taxes on the demand for tobacco products in a developing country. The price elasticities of demand suggested by their estimated tax elasticities are –1.42 for cigarettes and –1.00 for other tobacco products.
- *Turkey*: Tansel's (1993) estimates average –0.21 for short-run and –0.37 for long-run price elasticity of demand for cigarettes. This is an exception to the findings of most recent demand analyses for low- and middle-income countries, as they are lower than expected.
- *China*: Several recent studies produce estimates of the price elasticity of demand in China as a whole, Sichuan province, and Taiwan in ranges centering on –0.75.
- *South Africa*: Recent studies estimate the short-run price elasticity of demand for cigarettes at –0.59 and the long-run elasticity of demand at –0.69.

- *Zimbabwe*: A recent study estimates a price elasticity of demand for cigarettes of –0.85.
- *Brazil*: A study by Costa e Silva (1998), using limited data, produces a suggestive result for price elasticity of cigarette demand of –0.11 in the short-run and –0.80 in the long-run.

Income

Early analyses of the demand for cigarettes in industrialized countries find significant and positive income elasticities of demand, while more recent studies find insignificant and negative income elasticities. In the United States, for example, the income variable has a statistically significant positive impact on cigarette consumption, though it was negatively significant during the 1980's and 1990's. When United States data from the 1960's to the 1990's is combined, income is statistically insignificant. This suggests that tobacco products have moved, over the past 30 years, from being a superior good (or at least a normal one) to one preferred more and more by those in lower- to lower-middle income categories. This may be due to higher education levels of those in the higher income groups, which in turn brings increased awareness and appreciation of the health risks of smoking.

In some low- and middle-income countries, by contrast, tobacco products (particularly manufactured cigarettes as opposed to hand-roll cigarette tobacco, *bidis*, and *kreteks*) still have the status of superior goods, and hence positive income elasticity of demand, as found in the following studies:

- Chapman and Richardson (1990) find strong, positive effects of income on demand for both cigarettes and other tobacco products in Papua New Guinea.
- Tansel (1993) finds a strong, positive effect of income on cigarette demand in Turkey.

Studies from other low- and middle-income countries report results for income ranging from a statistically significant positive impact on tobacco product consumption to a significantly significant negative impact.

Advertising and Promotional Activity

The impact of advertising and promotion is by far the most controversial topic in the analysis of demand for tobacco products. Quantifying this impact can be very difficult, and it is important to conduct background research not only to achieve clarity on the nature, extent, and targeting of advertising and promotion of tobacco products, but to also avoid the methodological pitfalls that have limited the usefulness of so many previous studies of the topic. (Refer to the **Conduct Background Research** chapter for further discussion on this matter.) Even then, the results may not be significant or meaningful. Exercise careful judgement as to whether the inclusion of advertising and promotion in the demand specification is worthwhile.

The Nature of Tobacco Product Advertising and Promotion

Cigarettes dominate tobacco product marketing, as they are one of the most heavily advertised and promoted products in the world. In the United States, for example, the cigarette industry spent US$5.1 billion on advertising and promotion activities in 1996; as a percentage of sales, these expenditures have increased dramatically since 1980. Advertising and promotion occur in several forms:

- *Advertising* includes traditional advertising in the cinema and on television, radio, billboards, and posters; in newspapers, magazines, and transit facilities; and most recently on the Internet.
- *Promotion* covers a wide variety of activities, including: promotional allowances to retailers; point-of-purchase materials; direct mail advertising; distribution of free samples, coupons, and specialty or novelty items; multiple pack promotions and retail value-added offers; endorsements; sponsorship of cultural, sporting, and other entertainment events; and sponsorship of community and other organizations.

The Impact of Tobacco Product Advertising

The impact of smoking advertisements is extensively debated by public health advocates and the tobacco industry:

- Public health advocates maintain that cigarette advertising and promotion encourages smoking in aggregate and is a significant factor in initiating smoking among youth.
- Tobacco product manufacturers argue that cigarette advertising has no impact on aggregate cigarette consumption, but simply affects market share of particular cigarette brands while providing useful information to smokers about brands, including their nicotine and tar contents.

Public health advocates contend cigarette advertising and promotion *directly* influence cigarette consumption, in that:

- Children and young adults are enticed to experiment with smoking and to initiate regular smoking.
- Current smokers' willingness to quit smoking is reduced.
- Smokers increase their daily cigarette consumption because advertising serves as a cue or stimulus to smoke.
- Former smokers are induced to resume the habit because advertising reinforces the attractions of smoking.

Further, it is argued that cigarette advertising and promotion *indirectly* influence smoking by:

- discouraging a full discussion of the health consequences of cigarette smoking in media dependent on tobacco advertising
- contributing to a social environment in which smoking is perceived to be socially acceptable
- discouraging institutions dependent on tobacco industry promotional and other support from creating political opposition to strong tobacco control policies.

The Methodology of Econometric Analysis of Advertising and Promotion

Of the above direct and indirect mechanisms, economists have empirically tested only the first indirect mechanism. Strong evidence finds that, in the United States, coverage of the hazards of smoking is significantly diminished in magazines receiving an increasing share of advertising revenue from tobacco companies.

There are numerous econometric studies of the impact of cigarette advertising on cigarette demand, mostly for the United States and European Union countries. No consensus has emerged from this research, due to problems with the design of the studies.

Schmalensee (1972) analyzed cigarette advertising at both the firm and industry levels in the early 1970's, and makes three important suggestions:

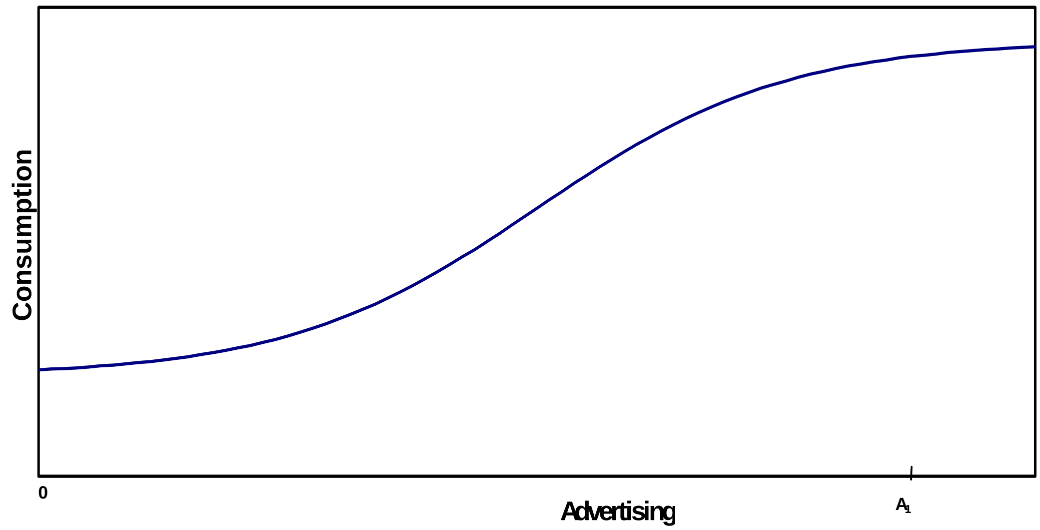
- A tobacco company's advertising expenditures may be based on current cigarette sales, making cigarette advertising expenditure endogenous. Failing to account for this endogeneity leads to biased estimates of the impact of advertising on demand.
- Failing to account for the cumulative or "stock" effects of advertising can lead to an omitted variables problem, although the evidence is mixed concerning the durability of cigarette advertising.
- The measure of cigarette advertising used as an explanatory variable is the ratio of cigarette advertising to total advertising.

Few studies follow Schmalensee's suggestions: nearly all treat cigarette advertising expenditure as exogenous, while most use absolute or per capita measures of cigarette advertising expenditure. It is therefore not surprising that results from this research are inconclusive.

Include advertising as an independent variable only when using quarterly or monthly data.

The mixed evidence from studies using aggregate data suggests that aggregate cigarette advertising has a small or negligible effect on aggregate cigarette sales. Apart from the methodological shortcomings discussed above, however, it has been pointed out that advertising expenditure is subject to diminishing marginal productivity, and that the "advertising response function" therefore takes the form of an S-shaped curve, shown in Figure 3.1. In highly concentrated cigarette markets with limited price competition, where the "personality" of brands created by advertising is important to

Figure 3.1
The Advertising Response Function



Source: Saffer (1999)

consumers, annual aggregate advertising expenditure is typically raised to a level (for example, level A_1 in Figure 3.1) where the marginal impact of total advertising expenditure on cigarette demand is negligible. This is why studies using annual aggregate data on advertising expenditure generally find it to have an insignificant influence on tobacco product demand. Advertising should thus be included as an independent variable only when quarterly or monthly data are being used.

Other methodological shortcomings of econometric studies of the impact of cigarette advertising on cigarette consumption include:

- the lack of appropriate measures of advertising exposure and other problems with the measures of advertising employed
- the failure to distinguish between the impacts of advertising and promotional activities
- problems with simultaneity between advertising expenditures and sales
- the omission of other key variables, such as health information or "counter-advertising" campaigns taking place at the same time
- concentration on restrictions in one or two advertising media, without controlling for the ability of cigarette manufacturers to shift expenditure towards other media and into promotional activity, and to develop new marketing approaches[6]

[6] In the United States, for example, bans on tobacco advertising via broadcast media caused the proportion of total advertising and promotional expenditure channeled into traditional advertising media to fall from 87

- failure to account for the fact that expenditure on advertising campaigns may be committed (and thus enter advertising statistics) in one time period, but be spent only during the following several time periods

More appropriate approaches include the examination of much more disaggregated data and the analysis of non-marginal changes in advertising expenditures, such as those resulting from significant restrictions or complete bans on cigarette advertising and promotion.

A number of country-specific studies examine the impact on smoking of restrictions and bans on cigarette advertising. In general, results suggest that partial advertising bans lead to temporary reductions in cigarette smoking, but have little effect in the long-run, while more extensive restrictions and complete bans on cigarette advertising combined with strong health warnings on cigarette packs lead to more permanent reductions in smoking.

It should be clear that there are many ways of modeling the impact of tobacco product advertising and promotional expenditure. For example, if the introduction of a health information campaign significantly counteracts the influence of tobacco product advertising and promotion, specify a slope dummy to multiply with the variable AD_t in Equations 3.7–3.9. Depending on one's view of the most plausible way to model the influence of the health campaign in question, the slope dummy can take the value 1 prior to the start of the campaign, and some value less than 1 (whether constant, declining, or increasing to 1) thereafter.

Nicotine Addiction and the Role of Past and Future Demand

Until the early 1980's, economists either ignored the addictive nature of goods (such as cigarettes) when estimating demand, or assumed that behaviors (such as smoking) were irrational and could not be analyzed in the rational, constrained, utility-maximizing framework of economics. However, two decades of econometric research has demonstrated that the demands for addictive substances are not exceptions to the basic laws of economics—in other words, the price elasticity of demand for tobacco products is negative and significantly different from zero.

For econometric purposes, models of addiction are divided into two basic categories of addictive behavior: "myopic addiction" and "rational addiction."

percent in 1974 to 10 percent in 1996—even though total advertising and promotional expenditure increased dramatically during that period.

Myopic Addiction Models

Myopic addicts recognize that their present addictive consumption decisions are determined by past consumption; but when making current choices, they ignore the impact of current and past consumption decisions on future consumption.

Some myopic addiction models treat preferences as endogenous, allowing them to change in response to past consumption (and in some cases to other factors, such as advertising). Other myopic addiction models allow past consumption to influence current consumption via an accumulated stock of past consumption.

Myopic addiction models predict that the long-run price elasticity of demand for tobacco products will be larger than the short-run price elasticity of demand (in absolute value).

Rational Addiction Models

Where myopic addiction models assume that addicts naively ignore future implications of their decisions, rational models work under a contrasting assumption. "Rationality" in the context of addiction means that addicts take account of the determination of future consumption by past and current consumption in their utility maximization process.

In other words, myopic addicts apply an infinitely high rate of discount to the future, while rational addicts consider future implications, although perhaps applying a high (but not infinite) discount rate.

The foremost model of rational addiction is that of Becker and Murphy (1988), in which utility is determined by current addictive consumption, current non-addictive consumption, and the stock of past addictive consumption. Several studies in the United States, Australia, and Finland, based on this model, find evidence that cigarette smoking is an addictive behavior and that smokers do not behave myopically.

Critiques of the Rational Addiction Model

There is criticism about several of the rational addiction model's assumptions, particularly that addicts have perfect foresight of the consequences of addiction. This does not seem entirely plausible.[7]

However, apart from price-responsiveness aspects, some features of the rational addiction model explain certain phenomena. One implication of the model is that efforts to reduce current consumption lead to reductions in utility. These costs of quitting smoking help explain the apparent inconsistency between the expressed desire of smokers to quit smoking and their continuation of cigarette smoking.

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[7] Indeed, as pointed out in *The Economic Case for Demand Intervention* section of the **Define the Objectives of the Analysis** chapter, the observation of widespread "information failures" regarding the health consequences of smoking and the risk of addiction provide an economic rationale for government intervention in the tobacco market.

Evidence from econometric studies in low- and middle-income countries includes the following:

- Tansel (1993) shows that lagged cigarette consumption has a positive and significant impact on current cigarette consumption in Turkey, consistent with the assumption of myopic addictive behavior.
- Hsieh and Hu (1997) estimate several alternative specifications for Taiwan, including one allowing for myopically addictive behavior. Current smoking is positively related to past consumption, consistent with myopic addiction.
- Van der Merwe's (1998) estimates for South Africa do not support the hypothesis of rational addiction.

In common with studies of high-income countries, studies that estimate models of addictive behavior in low- and middle-income countries provide mixed support for the hypothesis of rational addiction, but are more generally supportive of myopic addiction. This implies that the long-run reductions in cigarette smoking and other tobacco use resulting from a price increase exceed the short-run effects.

Time Trend

Aggregate demand for tobacco products varies with time—if there is no variation in demand over time, there is no point in regressing a time-series of aggregate demand on a set of independent variables. A time trend is often specified among the independent variables in previous econometric analyses of tobacco product demand. This is typically justified on the grounds that:

- Previous studies include a time trend.
- It is important to take into account a secular trend in tobacco product demand in the population concerned.

The first justification is hardly adequate. There must be sound *a priori* theoretical and practical reasons for including an independent variable in the demand specification, and blindly following the examples of others is not a good idea.

Regarding the second justification, note that there is actually no such thing as a "secular trend" in demand for tobacco products. Changes in demand for tobacco products are driven by such factors as price, income, advertising, addiction, counter-advertising, and smoking restrictions (as discussed in this and the following sections). A change in aggregate demand for tobacco products over time, and not explained by such factors, can only be driven by some other explanatory variable(s).[8]

[8] For example, change in demand can be due to a change in the demographic structure of the sample population. It is suggested that a major determinant of the decline in the prevalence of smoking in Australia during the 1970's and 1980's was the decline of a generation of male smokers who were addicted to nicotine during World War II, when cigarettes were freely supplied to the armed forces.

It makes little sense to say that demand for tobacco products is influenced simply by the passage of time—except in the case of non-stationarity of the data (i.e., when a time-series shows (usually an upward) drift or deterministic trend over time). It is important to test for data non-stationarity, and if appropriate to apply cointegration regression techniques (see the *Apply Tests for Non-Stationarity and Cointegration, and Specify Error-Correction Models* section of the **Another Demand Model** chapter), without including a time-trend variable in the demand model specification.

If the variables are stationary, or non-stationary but not cointegrated, include a time trend in the initial demand specification in order to test whether this variable picks up the influence of some other factor or factors not included. If it does, identify and specify that variable in the demand specification and determine the impact this has on the estimation results. Follow this procedure:

1. Regress trend-stationary variables on time and their (stationary) residuals used as substitute time-series. Difference non-stationary variables until they are stationary.
2. Include a time trend variable in the demand specification along with the now stationary variables in order to test the influence from any omitted variables.
3. If the time trend variable is significant, specify and estimate again the demand model with the original data variables in order to capture the influence of the formerly omitted variable. In the case of non-stationary variables, be alert to the dangers of spurious regressions.

Expect Results for Qualitative Independent Variables

Health Information and "Counter-Advertising"

The release of the first scientific evidence of the health consequences of smoking in the United States in the early 1950s, and the first U.S. Surgeon General's report on smoking and health in 1964, received substantial media coverage and public attention in the United States. Since then, the impact of these "health scares" on smoking has received extensive econometric analysis, and the general conclusion is that cigarette smoking falls significantly in response to any new information on its health consequences. For example, it is estimated that the U.S. Surgeon General's report of 1964 led to an immediate five percent decline in aggregate cigarette consumption. Further, U.S. per capita tobacco consumption was about 39 percent lower in 1978 than it would have been without the two health scares (Chaloupka and Warner, 1999).

The evidence linking cigarette smoking to morbidity and premature mortality leads to a number of public policy efforts to disseminate information on the health consequences of smoking (Chaloupka and Warner, 1999), including:

- *Warning labels on cigarette packaging and advertising*. Non-economic evidence from the United States and other countries suggests that multiple, strong, and direct messages that are prominently displayed are effective in discouraging smoking. The limited econometric analysis conducted on the impact of health warning labels suggests that they have led to small but significant reductions in cigarette smoking.
- *Mass-media "counter-advertising" campaigns*. These have been widely used to discourage smoking and other tobacco use. In the United States, several states have earmarked cigarette tax increases to fund health education campaigns to reduce cigarette smoking. Econometric analyses of anti-smoking publicity and paid counter-advertising in the United States and Finland, the United Kingdom, Greece, Turkey, and Australia generally conclude that such campaigns have significantly reduced cigarette smoking.

Little econometric analysis of this issue has been performed in low- and middle-income countries, although Tansel (1993) finds negative and significant effects on cigarette demand in Turkey of various indicators of health information.

As with all qualitative variables, there are many ways to model the impact of the health campaign intercept dummy variable D_n included in the demand specifications given in the **Specify the Demand Function** chapter. For example, if the influence of the health campaign is expected to diminish rapidly after its inception, rather than have D_n consistently maintain a value of 1 from year *n,* follow Warner's (1977) example and set $0.5^{(t-n)}$ as its value. This variable therefore assumes values of 1 in year *n*, 0.5 in year *n*+1, 0.25 in year *n*+2, and so on. Be sure to apply knowledge of conditions in specific tobacco product markets in order to model the impact of this and other qualitative variables in the most appropriate and effective way.

Smoking Restrictions

As information on the health consequences of exposure to environmental tobacco smoke (ETS)—also called "passive smoking"—becomes widespread, governments at national, sub-national, and local levels in several industrialized countries are adopting policies to limit smoking in public areas and private workplaces. Although these restrictions are intended to reduce non-smokers' exposure to ETS, they also lead to significant reductions in cigarette smoking, since they reduce opportunities to smoke and thereby raise the "cost" or "full price" of smoking. Evidence suggests that this is particularly true for restrictions on smoking in the workplace. In addition, restrictions on smoking can help alter the social acceptability of smoking.

Several recent econometric studies of the impact of smoking restrictions on cigarette demand in the United States and elsewhere find that restrictions on smoking in public areas and private workplaces reduce both smoking prevalence and average daily cigarette consumption among smokers. However, a possible methodological complication should be noted: it is found that smoking restrictions may be endogenous with respect to cigarette consumption. For example, U.S. states with the strongest smoking restrictions (those with limits on smoking in private workplaces) are also the states in which anti-smoking sentiment is relatively high and smoking is relatively low. After controlling for this, recent econometric studies show mixed results on whether the strongest smoking restrictions significantly impact cigarette demand. Overall, however, the available evidence tends to suggest that comprehensive restrictions on smoking in public places significantly reduce smoking even after accounting for their potential endogeneity.

Note that if an index of smoking restrictions, as suggested in the *Prepare the Data* section of the **Build the Data Set** chapter, cannot be compiled due to lack of data, specify a dummy variable in Equations 3.1–3.9 to control for the introduction of such restrictions in place of SR_t, as follows:

> D_n = an intercept dummy for the introduction of comprehensive restrictions on smoking in public places and private workplaces in time period *n*; 0 prior to time period *n*, 1 from time period *n* onwards.

Include Other Independent Variables

If the relevant data are available in adequate quality, include other independent variables in the demand specification, particularly when using quarterly or monthly data and the number of degrees of freedom is therefore not a constraint.

Prices of Complements and Cross-Price Elasticity of Demand

Until recently, there has been little empirical analysis of the relationship between tobacco product consumption and consumption of possible complements, such as alcohol. One exception is a study using Spanish cross-sectional household survey data (Jimenez and Labeaga, 1994). It concludes that alcohol and tobacco are complements, and that higher excise taxes on alcohol reduce tobacco consumption. However, whenever evaluating the relationship between consumption of tobacco products and possible complements, take care to distinguish between correlation and causality; the fact that consumption of two products is positively correlated is not sufficient to prove that they are complements.

Prices of Substitutes and Cross-Price Elasticity of Demand

Substitution Among Tobacco Products

Substitutes for cigarettes among tobacco products include pipe tobacco, cigars, *bidis*, *kreteks*, and smokeless tobacco products in the form of snuff and chewing tobacco. Relatively little econometric analysis of possible substitution effects among tobacco products has been done. However, recent cross-sectional studies in the United States finds evidence of substitution among tobacco products, in that higher cigarette prices have a positive and significant effect on the prevalence of smokeless tobacco use (Ohsfeldt, Boyle, and Capilouto, 1999).

With respect to developing countries, Chapman and Richardson (1990) find strong cross-tax impacts between cigarettes and other tobacco products in Papua New Guinea, indicating that cigarettes and other tobacco products are substitutes in that country. Their findings predict that much of the reduction in cigarette tobacco consumption achieved by a cigarette tax increase is offset by an increase in consumption of other tobacco products. Studies in other low- and middle-income countries also suggest that cigarettes and other tobacco products are substitutes for one another.

Substitution between Tobacco Products and Other Substances

Only one study has been conducted in the United States on cross-price elasticity of demand between tobacco products (specifically, cigarettes) and the possible non-tobacco substitute of marijuana among youth, using individual-level cross-sectional data (Chaloupka *et al*, 1999). It finds that marijuana is more likely to be a complement than a substitute for cigarettes.

It appears that no econometric analysis of possible substitution effects between tobacco products and possible non-tobacco substitutes, such as marijuana, has been conducted for low- and middle-income countries. Assuming that data on demand and street prices (or suitable proxies for them) can be estimated for marijuana, a carefully conducted econometric analysis is of interest to tobacco control advocates in countries like South Africa, which has a large and apparently thriving clandestine trade in marijuana.

References and Additional Information

The following are sources of information to refer to for background discussions of tobacco demand. See the **Additional References** chapter for a complete description of these and other sources.

> Saffer and Chaloupka (1999) offer an excellent overview of the debate on the impact of advertising and promotion on the demand for tobacco products, and have developed a very

useful guide to the difficulties involved in econometric research on the topic.

Keeler, Hu, Barnett, and Manning (1993) apply the theory of rational addiction to monthly aggregate data from California. In so doing, they provide a useful and comprehensive overview of many of the practical issues involved in time-series analysis of demand for tobacco products.

Bardsley and Olekalns (1999) institute a rigorous and thorough application of the theory of rational addiction to annual aggregate data on tobacco product consumption in Australia, supplemented by data on advertising, regulatory intervention, and demographic factors.

VIII. Another Demand Model: Error Correction Models and Diagnostic Tests

Definitions

Cointegration

Cointegration can be defined as follows:

- In *economic* terms, two or more time-series are cointegrated if the series move together over time and the differences between them are stable (i.e., stationary), even though each series contains a stochastic trend and is therefore non-stationary. Hence, cointegration reflects the presence of a long-run equilibrium to which an economic system converges over time. The differences (or error terms) in the cointegrating equation are interpreted as the disequilibrium error at each particular point in time.
- In *econometric* terms, two or more time-series which are non-stationary of order I(1) are cointegrated if a linear combination of these series exists that is stationary, or I(0). The vector of coefficients creating this stationary series is the cointegrating vector.

Aggregate consumption and aggregate income are good examples of two cointegrated economic time-series. If they are not cointegrated, consumption can drift significantly above or below income in the long-run, as consumers irrationally overspend or spend an unusually low proportion of their income, respectively.

Collinearity

Collinearity refers to the existence of a linear relationship between two explanatory variables in a regression model. In other words, the coefficient of correlation between the two variables will tend towards unity. If more than two explanatory variables within a regression are linearly related, the term "multicollinearity" is used.

A high degree of collinearity or multicollinearity is potentially problematic because a linear relationship between two or more explanatory variables makes it difficult to separate out the influence each variable has on the dependent variable. The practical consequences of high multicollinearity include large variances and covariances in ordinary least squares regression estimators, wider confidence intervals for sample population parameters, seemingly insignificant t-ratios, and sensitivity of estimators to small changes in the data.

Because multicollinearity is basically a sample phenomenon, and the extent thereof will vary from sample to sample, there is no unique means of testing for it. Instead, several rules of thumb can be applied to gauge the extent of multicollinearity. There is little one can do about serious multicollinearity, as the remedies available generally have their own potentially serious shortcomings. For example, dropping one of the collinear explanatory variables may lead to specification bias. However, researchers should be alert to the difficulties that a high degree of multicollinearity can impose on the interpretation of regression results.

Error-Correction Model

A long-run cointegration relationship between two or more non-stationary data series corresponds to an embedded *error-correction mechanism*, which compensates for short-run deviations of the data from the equilibrium of the long-run model. In other words, if the system deviates from equilibrium in the short-run, short-run demand relationship will intervene to "correct" this "error" and move the system back towards equilibrium. Both the Engle-Granger and Johansen procedures (need references) can be used to estimate the coefficients of this dynamic *error-correction model* (ECM), thereby obtaining the parameters of the short-run demand relationships present within the model.

Johansen Cointegration Procedure

In effect, testing for cointegration involves determining whether there is a long-run relationship between non-stationary variables. There are two main approaches to this:

- The *Engle-Granger two-step method* is a single-equation approach, is relatively straightforward, and is available in most econometric software packages.
- The *Johansen procedure*, a systems approach, is more complex than the Engle-Granger method and is available only in some econometric software packages. The econometric literature has given this procedure a lot of attention, and it is currently regarded as the state-of-the-

art in econometric analysis of time-series—but it requires careful handling.

The Johansen procedure treats all variables as potentially endogenous, modeling each variable as an unrestricted vector autoregression (VAR) involving a number of lags. An advantage is that dynamic relationships among endogenous variables are modeled without strong *a priori* restrictions. Using a vector error-correction model (VECM), differences in these endogenous variables are expressed in terms of short-run changes (differences) and long-run changes (levels). These results are then decomposed into coefficients representing the speed of short-run adjustment to disequilibrium, and coefficients representing the long-run cointegrating relationship.

Researchersshould carefully consider the following characteristics of the Johansen procedure:

- The Johansen procedure is extremely data-intensive, and is intended for application to long time-series. Therefore, apply it only to quarterly or monthly data. Results from annual data sets are likely to be subject to significant small sample bias and error.
- Illogical model specifications may result because the Johansen procedure tries to make the model as general as possible and its use of a VAR-type model places no prior restrictions on potentially endogenous variables. For example, the procedure may include lags for particular variables (such as income) that are not plausible explanatory variables in relation to the demand for tobacco products.

Johansen's cointegration test can operate under several sets of assumptions regarding the presence or absence of deterministic trends present in the data, any of which can be specified in advance by users. Exogenous variables (such as seasonal dummies), if any, should also be specified in advance when applying the test.

Price Endogeneity

The market for tobacco products consists of the interaction of supply and demand. In a competitive market, both price and quantity will vary until the market clears (i.e. quantity supplied is equal to quantity demanded at a given price). Price and quantity influence each other (for example, if the price asked by suppliers falls, the quantity demanded by consumers increases) until the market-clearing quantity and price are reached. In such a situation, the market price of tobacco products is determined by the interaction of demand and supply *within* the market itself, and price is considered *endogenous*, or "determined within".

If the price of tobacco products is set *outside* this interaction of supply and demand (for example if prices are set by legislation completely independently of demand or supply), price is said to be *exogenous*, or "determined outside".

If price is endogenous, the simultaneous determination of quantities and prices of tobacco products bought and sold in competitive markets causes an *identification problem*—one can never be sure that two different combinations of market-clearing price and quantity both lie on the same demand curve. Failure to account for this in regression analysis of demand will result in biased estimates. However, if it is reasonable to assume that the supply of tobacco products is infinitely elastic (and hence that price is basically exogenous), there is no identification problem—it is certain that every combination of price and quantity in the data lies on the demand curve.

In many low- and middle-income countries it may indeed be the case that the supply of tobacco products is infinitely elastic, particularly for those countries that must import the bulk of their tobacco leaf and/or manufactured tobacco products. Most countries are small relative to the global market for tobacco leaf and tobacco products, and tobacco companies allocate their (finite) supplies of both to the countries that pay the highest prices. Once the marginal demander of tobacco is not willing to pay these prices, supplies are shipped to another country. In these circumstances, supply within many countries can be characterized as infinitely elastic.

If it is *not* reasonable to assume that supply is infinitely elastic—in other words, if price is endogenous—appropriate econometric techniques, such as the use of instrumental variables or simultaneous equation modeling, should be applied.

Hausman's test can be used to determine whether price is exogenous or endogenous.

Stationarity

Time-series data variables are characterized with respect to the *stationarity* of their underlying data generation processes. Accordingly, a particular data series can be categorized as being one of the following:

- *Stationary*: The data series has a constant mean and variance that are independent of time. In other words, the series fluctuates around its mean value within a finite range, and does not show any distinct trend over time.
- *Trend-stationary*: The data series has a constant variance around a deterministic (i.e., fixed) time trend. The series fluctuates around the time trend within a finite range.
- *Non-stationary*: The data series does not have a constant mean or a constant variance, but follows a stochastic (i.e., random) time trend, drifting either upwards or downwards over time, without being confined within a finite range. Variance increases with sample size.

Most economic time-series are not stationary, but trend upwards over time. It is important to control for such trends in regression analysis, otherwise spurious regressions can result. The results of such spurious regressions would suggest that there is a statistically significant long-term relationship between the variables in the regression model, when all that is being reflected is a correlated time trend rather than a meaningful causal relationship.

It is therefore important to test time-series data for non-stationarity, and if it is present, to apply the appropriate econometric techniques (such as cointegration regression) to control for it.

Assumptions and Requirements

Readers of this tool should have some background knowledge on issues surrounding tobacco products and policies. In addition, note that every country faces its own more or less unique patterns of demand for tobacco products. Researchers in a particular country or region should therefore try to obtain detailed background knowledge of the local tobacco market to help them accurately model and analyze the demand for tobacco products. This background research should provide information on the social, economic, and institutional characteristics of the demand for tobacco products.

Readers with little knowledge of economics or econometrics will be able to follow only the non-technical sections of this tool. In contrast, researchers intending to undertake quantitative analysis of the demand for tobacco products should be professional economists with postgraduate-level training in econometrics and several years of practical experience in econometric analysis. The components of and resources required for a quantitative analysis of the demand for tobacco products are discussed in the section on *Design an Analysis of Demand Study* in the **Define the Objectives of the Analysis** chapter.

Prepare for Regression Analysis

Before performing regression analysis using the demand models described in the **Specify the Demand Function** chapter, state in advance the expected signs and ranges of the coefficients to be estimated. The expected results should be informed by the in-depth understanding of conditions in the relevant tobacco product market, as obtained during the background research phase. Refer to the **Conduct Background Research** chapter for additional information.

Just as importantly, have a clear work plan in mind from the outset regarding the econometric tests and regression techniques to apply, the order in which they are applied, and the alternative techniques to use if there are problems with the results. It is traditional to begin with OLS estimates, check them for "pathologies" such as model misspecification, autocorrelation, and heteroscedasticity, and then apply whichever econometric techniques promise to solve the problems.

Given the potentially serious impact of data non-stationarity on time-series analysis, however, a more desirable sequence is recommended, as follows:

1. Test all variables for non-stationarity (see the *Non-Stationarity and the Problem of Spurious Regression* subsection of this chapter).
   a. If two or more variables are non-stationary, test for cointegration (see the *Cointegration Relationships* subsection of this chapter).
      i. if a cointegration relationship exists, take its parameters as long-run model results, and estimate a short-term error-correction model (see the *Estimate an Error-Correction Model and Short-Run Demand Relationship* subsection of this chapter).
      ii. if a cointegration relationship does not exist, apply OLS regression, with a time-trend variable included in the initial demand specification used, being alert to spurious regression results.
   b. If one or no variables are non-stationary, apply OLS regression, with a time-trend variable included in the initial demand specification used.
2. Apply appropriate specification and diagnostic tests (see the *Administer Specification and Diagnostic Tests* section of the **Specify the Demand Function** chapter).
3. Analysis regression results and relevant specification and diagnostic test results, and decide whether:
   a. alternative regression techniques should be applied, and/or
   b. the functional form of the demand model should be re-specified, and/or
   c. other variables should be included or currently included variables omitted, and/or
   d. other data variables should be substituted where appropriate (assuming that accurate proxy data series are in fact available).
4. Once valid regression results have been obtained, calculate and review elasticities of demand (see the **Review and Understand the Results** chapter).

Apply Tests for Non-Stationarity and Cointegration, and Specify Error-Correction Models

A common and potentially serious problem in time-series analysis is non-stationarity, which can result in spurious regressions. Cointegration regression addresses this problem.

Cointegration regression is difficult, and a comprehensive treatment of the topic cannot be provided in this tool. However, the remainder of this chapter summarizes salient points and highlights potential difficulties and issues. (Note: time trend variables are excluded from stationarity tests and cointegration regression specifications.)

Non-Stationarity and the Problem of Spurious Regression

It is necessary to consider the nature of the processes that generate the time-series data variables used in demand analysis, for these may influence the validity of the regression results obtained. Time-series data variables are characterized with respect to the stationarity of their underlying data generation processes, as follows:

- *Stationary*: The data series has a constant mean and variance that are independent of time. In other words, the series fluctuates around its mean value within a finite range, and does not show any distinct trend over time.
- *Trend-stationary*: The data series has a constant variance around a deterministic (i.e., fixed) time trend. The series fluctuates around the time trend within a finite range.
- *Non-stationary*: The data series does not have a constant mean or a constant variance, but follows a stochastic (i.e., random) time trend, drifting either upwards or downwards over time, without being confined within a finite range. Variance increases with sample size.

Most economic time-series are not stationary, but trend upwards over time. It is important to control for such trends in regression analysis, otherwise spurious regressions can result. The results of such spurious regressions would suggest that there is a statistically significant long-term relationship between the variables in the regression model, when all that is being reflected is a correlated time trend rather than a meaningful causal relationship.

The deterministic time trend in a trend-stationary variable is removed by regressing the variable on time. The resulting residuals form a new trend-free, stationary variable. Alternatively, the trend is controlled by including a deterministic time trend in the regression equation.[9] In contrast, regressing a non-stationary variable on a time trend generally does not result in a stationary variable. Instead, the variable must be differenced until it is stationary; the number of times the series must be differenced corresponds to the number of ‘unit roots’ present in the data generating process underlying the time-series. That is, if a series must be differenced *d* times before it becomes stationary,

[9] Refer to the *Time Trend* subsection of the **Review and Understand the Results** chapter for a discussion of the role of time trend variables.

it contains *d* unit roots and is said to be integrated of order *d*, denoted I(d).

It is important to test time-series data for the presence of unit roots, and to apply the appropriate econometric techniques to control for non-stationarity of variables. In this regard, cointegration regression avoids spurious regressions, which are a major problem of conventional econometric analysis of time-series data.

Test for Non-Stationarity

Two commonly used tests for unit roots, available in most popular econometric software packages, are the Augmented Dickey-Fuller test, and the Phillips-Perron test (reference).

The Augmented Dickey-Fuller Test

There are two practical issues to face in performing the Augmented Dickey-Fuller (ADF) test (reference). First, specify within the econometrics software the number of lagged first difference terms to add to the test regression (this is necessary to remove any serial correlation in the residuals). The number of lags of the dependent variable included in the regression model has a major impact on the critical values assumed by the test. Second, decide what other exogenous variables (e.g., a constant, a constant and a linear time trend, or neither) to include in the test regression. These assumptions about the underlying data generation process lead to different critical values of the ADF test. The following practical guidelines apply, depending on how the relevant series looks when graphed in both levels and differences:

- If the series seems to show a trend (deterministic or stochastic), specify both a constant and a trend for the test regression.
- If the series does not seem to show any trend and has a non-zero mean, include only a constant.
- If the series seems to be fluctuating around a zero mean, do not include both a constant and a trend.

Alternatively, apply a sequential testing procedure to avoid arbitrary test results; the ADF test is performed with intercept, trend, and lagged variables included. If a variable is not significant at the 10 percent level, the least significant variable (as measured by the t-value) is removed, and the test equation is run again without it.[10] Repeat this process until the remaining variables are significant at the 10 percent level.

The ADF test is a useful indicator of stationarity, but regard its results with caution, since the test may not be sufficiently robust

[10] The only exception to this procedure is the intercept: if the trend variable is significant while the intercept is not, the intercept is not excluded from the test equation.

in small samples to discriminate between non-stationary and trend-stationary data generation processes.

The Phillips-Perron Test

As with the ADF test, it is necessary to specify the exogenous variables to include in the test regression (e.g., a constant, a constant and linear trend, or neither). Also specify the number of periods of serial correlation to include. In this regard, most econometric software packages usually default to a value based on the number of observations used in the test regression.

Monte Carlo simulations demonstrate that no one unit root test is unequivocally better than another. Keep in mind that the power of these tests of stationarity is quite low, so take care in interpreting the results.

An example of ADF test results for annual aggregate and per capita cigarette consumption data is provided in Table 3.7. Both aggregate cigarette consumption (measured in million of packs of 20 per annum) and per capita cigarette consumption (measured in packs per annum per person aged 15 years and over) are found to be non-stationary in levels, but stationary in first differences, and are thus integrated of the first order—that is, I(1). Real per capita personal disposable income is stationary in levels—that is, I(0). This is a plausible result given the low economic growth rates of the South African economy, particularly during the second half of the sample period. Real aggregate personal disposable income is also stationary in levels. The real retail price of cigarettes is stationary in first differences, or I(1).

Hsieh, Hu, and Lin (1999) apply the ADF test to annual time-series data from Taiwan for the period 1966–1995, including a constant term and time trend in the test equation. The following

Table 3.7
ADF Test Results for South African Cigarette Demand Data, 1970–1998

Variable	Testing whether Stationary in:	Trend	Intercept	Number of Lags	T-value	Level of Integration
Aggregate cigarette consumption	Levels	No	Yes	1	–1.568	I(1)
Aggregate cigarette consumption	First differences	No	No	0	–2.936***	I(0)
Per capita cigarette consumption	Levels	No	No	1	–0.587	I(1)
Per capita cigarette consumption	First differences	No	No	0	–3.448***	I(0)
Real aggregate personal disposable income	Levels	Yes	Yes	1	–4.119***	I(0)
Real per capita disposable personal income	Levels	Yes	Yes	0	–4.192**	I(0)
Real retail price of cigarettes	Levels	Yes	Yes	0	3.176	I(1)
Real retail price of cigarettes	First differences	Yes	Yes	0	–3.763**	I(0)

*** Significant at the 1 percent level
** Significant at the 5 percent level
Source: Van Walbeek (2000)

variables are all I(1) in levels (and stationary in first differences):

- per capita cigarette consumption
- per capita consumption of imported cigarettes
- real average retail cigarette price per pack
- real average retail cigarette price per pack of domestic cigarettes
- real average retail cigarette price per pack of imported cigarettes
- the market share of imported cigarettes
- the participation rate of the female labor force

Interestingly, per capita consumption of domestic cigarettes and real per capita disposable income are I(0).

It is highly unlikely that only one time-series in a demand model is non-stationary. However, if this is in fact the case, do not apply further cointegration regression procedures; instead use OLS and subject the results to diagnostic testing (see the *Administer Specification and Diagnostic Tests* section of the **Specify the Demand Function** chapter). If two or more variables are non-stationary, proceed with cointegration testing and the estimation of an error-correction model.

Cointegration Relationships

Even if data series are non-stationary, it is possible to infer a long-term causal relationship between them if they are cointegrated. Cointegration can be defined as follows:

- In *econometric* terms, two or more I(1) time-series are cointegrated if a linear combination of these series exists that is I(0)—that is, stationary. The vector of coefficients creating this stationary series is the cointegrating vector.
- In *economic* terms, two or more time-series are cointegrated if the series move together over time and the differences between them are stable (i.e., stationary), even though each series contains a stochastic trend and is therefore non-stationary. Hence, cointegration reflects the presence of a long-run equilibrium to which an economic system converges over time.[11] The differences (or error terms) in the cointegrating equation are interpreted as the disequilibrium error at each particular point in time.

Aggregate consumption and aggregate income are good examples of two cointegrated economic time-series. If they are not cointegrated, consumption can drift significantly above or below income in the long-run, as consumers irrationally

[11] In this instance, "equilibrium" is understood as a steady-state relationship between variables that are themselves evolving over time.

overspend or spend an unusually low proportion of their income, respectively.

After determining which of the data variables are non-stationary (see the *Test for Non-Stationarity* subsection of this chapter), the next step is to test the I(1) data series for cointegration relationships.[12] In effect, this involves estimating the long-run relationship, if any, between the variables concerned, as discussed in the *Cointegration Testing: Estimate the Long-Run Demand Relationship* subsection of this chapter. Note that if there are *k* potentially endogenous variables in the system being estimated, each of which has one unit root, there can be anything from a zero to *k*–1 linearly independent cointegrating relationship. The presence of more than one cointegrating relationship in a demand system complicates the interpretation of relationships between the variables, but econometric software packages provide tests to highlight the most likely cointegration relationship.

Cointegration Testing: Estimate the Long-Run Demand Relationship

In effect, testing for cointegration involves determining whether there is a long-run relationship between non-stationary variables. There are two main approaches:

- The *Engle-Granger two-step method* is a single-equation approach, is relatively straightforward, and can be used in most econometric software packages.
- The *Johansen procedure*, a systems approach, is more complex than the Engle-Granger method and is not available in all econometric software packages (refer to the *Resources Required* subsection of the **Define the Objectives of the Analysis** chapter for recommended software packages). The academic literature gives this procedure a lot of attention, and it is currently regarded as the state-of-the-art in econometric analysis of time-series—but it requires careful consideration.

Engle-Granger Two-Step Method

First estimate a long-run equation with the data in levels, and then test the residuals for stationarity. If the residuals are in fact stationary, this is evidence that the long-run equation is cointegrated. This process estimates a static OLS regression model in order to discover the coefficients of the long-run stationary relationship between the non-stationary variables. Though the approach ignores short-run dynamic effects and the possibility of endogeneity, it is justified on the grounds that the OLS estimators are super-consistent (i.e., due to the presence of

[12] The presence of I(2) variables, fortunately uncommon, makes cointegration estimation more difficult. The most recent versions of some popular econometric software packages can now handle this, however.

cointegration they converge to their true values at a faster rate than conventional OLS estimators with stationary variables).

Johansen Procedure

The Johansen procedure treats all variables as potentially endogenous, modeling each variable as an unrestricted vector autoregression (VAR) involving a number of lags. An advantage is that dynamic relationships among endogenous variables are modeled without strong *a priori* restrictions. Using a vector error-correction model (VECM), differences in these endogenous variables are expressed in terms of short-run changes (differences) and long-run changes (levels). These results are then decomposed into coefficients representing the speed of short-run adjustment to disequilibrium, and coefficients representing the long-run cointegrating relationship. Carefully consider the following characteristics:

- The Johansen procedure is extremely data-intensive, and is intended for application to long time-series. Therefore, apply it only to quarterly or monthly data. Results from annual data sets are likely to be subject to significant small sample bias and error.
- Illogical model specifications may result because the Johansen procedure tries to make the model as general as possible and its use of a VAR-type model places no prior restrictions on potentially endogenous variables. For example, the procedure may include lags for particular variables (such as income) that are not plausible explanatory variables in relation to the demand for tobacco products.

Johansen's cointegration test can operate under several sets of assumptions regarding the presence or absence of deterministic trends present in the data, any of which can be specified in advance by users. Specify exogenous variables (such as seasonal dummies), if any, when applying the test.

Wherever practical, begin with the Johansen multivariate procedure rather than the Engle-Granger single-equation approach (except in the very unlikely case that only two variables are involved). Starting with a systems approach prevents consideration of only one cointegrating relationship between the variables, when in fact there can be more. Not allowing for the possibility of other cointegrating vectors results in inconsistent and inefficient estimates.[13]

Use the single-equation approach only when there is certainty of a single, unique cointegration vector, and when all the independent variables are known to be weakly exogenous. As this knowledge is seldom available in advance without thorough testing, it is generally safer to begin with the Johansen procedure wherever possible.

[13] The presence of more than one cointegrating relationship between variables can cause difficulty in practical economic interpretation of the causal relationship between variables.

A practical example of the difficulties involved in applying cointegration analysis is provided in Table 3.8. Both the Johansen and Engle-Granger methods are applied to test cointegration, but only the Engle-Granger results are published. While the overall superiority of the Johansen method is fully appreciated, the Engle-Granger results are relied upon instead for the following reasons:

- Data for all relevant variables are available only on an annual basis, giving a sample too small for the Johansen procedure to yield reliable results.
- *A priori* restrictions are placed on the specification of the demand model, and those restrictions are ignored by the Johansen procedure's unrestricted VAR model.
- The Johansen procedure's inclusion of lagged values of variables, such as income, in its model have little economic plausibility, particularly when using annual data.
- Preliminary tests using the Johansen procedure suggest more than one long-term relationship between the relevant variables, and it is difficult to interpret which is the more plausible.

Results from the Engle-Granger approach to cointegration testing of the data are provided in Table 3.8. Due to the non-stationarity of the data, the *t*-values are inflated and should be seen as indicative only.

Table 3.8
Cointegration Test Results for South African Cigarette Consumption Data, 1970–1998

Variable	Coefficient	T-value	Probability Value
Equation 1: Aggregate Annual Cigarette Consumption (Millions of Packs of 20)			
Constant	991.580	7.37	0.0000
Real aggregate personal disposable income	0.005	18.31	0.0000
Real retail price of cigarettes	–2.797	–12.65	0.0000
Dummy to neutralize data outlier value for 1982	198.000	4.43	0.0002
Dummy for increased tobacco regulation after 1994	–105.970	–2.38	0.0258
Adjusted R^2 = 0.986; DW = 1.633			
Equation 2: Per Capita Annual Cigarette Consumption (Packs per Annum per Person 15 and over)			
Constant	81.590	5.93	0.0000
Real per capita personal disposable income	0.002	2.38	0.0258
Real retail price of cigarettes	–0.130	–13.83	0.0000
Dummy to neutralize data outlier value for 1982	13.010	5.07	0.0000
Dummy for increased tobacco regulation after 1994	–3.130	–21.3	0.0435
Adjusted R^2 = 0.922; DW = 1.178			

Source: Van Walbeek (2000)

ADF tests are applied to the residuals to test for cointegration in Table 3.9, where the null hypothesis of no cointegration is rejected at the 10 percent level for Equation 3.1 (aggregate cigarette consumption), but not rejected for Equation 3.2 (per capita cigarette consumption). Given that the null hypothesis cannot be confirmed for Equation 3.2, the model is dropped and analysis continued with Equation 3.1.

Estimate an Error-Correction Model and Short-Run Demand Relationship

Engle-Granger Two-Step Method

The Engle-Granger method holds that a long-run cointegrating relationship corresponds to an embedded error-correction mechanism, which compensates for short-run deviations from the equilibrium of the long-run model. The second step of the Engle-Granger method estimates this dynamic error-correction model (ECM), obtaining coefficients of the short-run dynamic relationships within the model.

Van Walbeek's (2000) analysis yielding the error-correction model of aggregate cigarette consumption is detailed in Table 3.4. Because cigarette demand is estimated in first difference form, high explanatory power is not expected. However, all coefficients are highly significant and of the correct signs. The coefficient of –0.633 on the lagged residual indicates that, on average, about 63 percent of the deviation from long-run equilibrium is compensated for in the following year—a relatively rapid speed of adjustment.

Johansen Procedure

Once the Johansen cointegration test is applied to estimate the long-run demand relationship, the number of cointegrating equations obtained from the test is then input into the Johansen error correction model. As with the second step of the Engle-Granger method, this provides the parameters of the short-run demand relationships between the variables concerned.

Table 3.9
Result of ADF Tests for Cointegration on South African Annual Cigarette Consumption Models

Characteristic	Equation 1 (Aggregate Consumption)	Equation 2 (Per Capita Consumption)
Trend	No	No
Intercept	Yes	Yes
Number of lags	2	2
t-value	–4.22	–3.37
Critical ADF value at 10%	–4.10	–4.10
Critical ADF value at 5%	–4.50	–4.50
Critical ADF value at 1%	–5.31	–5.31

Source: Van Walbeek (2000)

Non-Stationary but Cointegrated Variables

If the non-stationary variables in a demand model are cointegrated, the application of conventional regression techniques is still valid. This procedure is followed by Hsieh, Hu, and Lin (1999) in their analysis of the demand for cigarettes (average number of cigarette packs bought annually by persons aged 15 and over) in Taiwan (see the *Test for Non-Stationarity* subsection of this chapter). They determine a cointegration relationship between the non-stationary variables, and then apply OLS and two-stage least squares (2SLS) to five distinct specifications of the demand model. The regression results are summarized in Table 3.3, along with diagnostic test results (see the *Administer Specification and Diagnostic Tests* section of the **Specify the Demand Function** chapter).

The authors note that their small data sample size (30 observations) requires estimates and test results to be treated with caution. Apart from illustrating real-life compromises due to data availability problems, however, the study provides a useful example of the following issues:

- Applying conventional techniques to cointegrated time-series.
- Using instrumental variable techniques to deal with simultaneous determination (see the *Apply Instrumental Variable Techniques* section of the **Specify the Demand Function** chapter).
- Using diagnostic tests (see the *Administer Specification and Diagnostic Tests* section of the **Specify the Demand Function** chapter).

References and Additional Information

The following are sources of information to refer to for background discussions of tobacco demand. See the **Additional References** chapter for a complete description of these and other sources.

Harris (1995) offers an excellent and accessible introduction to stationarity and cointegration, and provides a thorough guide to the practical difficulties involved in the application of cointegration techniques.

IX. Disseminate the Research Findings

Understand the Objectives of the Dissemination Phase

At this point of a study, demand analysis has been conducted using the best available data and the most appropriate econometric techniques. The objective of the dissemination phase, then, is to make these facts, the findings of the analysis, and an explanation of their analytical basis abundantly clear to all parties with an interest in tobacco control in the country concerned.

Once the study of the demand for tobacco products is finalized and results have been noted, communicate the findings to the following recipients:

1. the overall coordinators of the economic study, who will collate the results from the other economic analyses (e.g., taxation, smuggling, employment, and equity considerations) and produce an overall economic research report for dissemination to the other recipients
2. the body coordinating the country's tobacco control initiative as a whole
3. the country's policy makers responsible for implementing tobacco control measures
4. the wider target audience of people and organizations within that country and elsewhere with an interest in tobacco control
5. the academic community

In disseminating the findings of the demand study, observe the following issues:

- The analysis of the demand for tobacco products is but one component of a larger and more comprehensive study of the main economic issues of tobacco control in the country concerned.

- The audience interested in the dissemination of the research results consists of several broadly distinct groups. Their requirements for information from the study differ according to their professional, disciplinary, and functional backgrounds—in essence, according to their roles in (or in opposition to) tobacco control in that country.
- One of the characteristics differentiating these groups along functional lines is their understanding of, and experience in, economic and econometric analysis. When writing the economic study's research report, take into account the widely differing levels of technical detail at which particular professional groups can (and are willing to) absorb from the results of the study.
- It will be the task of the policy makers and analysts concerned with tobacco control, acting in consultation with the coordinators of the overall economic study, to use mass media to communicate the implications of the research results to the wider public.

Identify the Composition and Requirements of the Target Audience

Audience Sub-Groups

The composition of the audience depends on the objectives of the study, its scope, and its management and coordination structures. It is probably most useful to differentiate very broadly between them—along professional, disciplinary, and functional lines. On this highly simplified basis, divide the audience into three broad sub-groups.

Economists

This group includes:

- the overall leader of the economic analysis study, and colleagues working on other economic aspects of tobacco control (e.g., taxation, smuggling, employment, and equity issues)
- associates in other organizations, both domestically and overseas, invited to assist with and/or review the analysis (for example, members of the global tobacco control network providing technical support to tobacco control initiatives in their launch phase)
- economists in government ministries tasked to examine the research and its implications for economic and other policy (for example, officials of the Budget Office of the Ministry of Finance might be asked to investigate the fiscal implications of the research findings)

- economists in trade unions organizations, private sector chambers of commerce, industry employer associations, and other bodies representing labor and business, who will have an interest in exploring the wider implications of the research results

Other Professionals

These individuals analyze the implications of tobacco control:

- health care professionals from the Ministry of Health (tasked with epidemiological monitoring of preventable diseases, preventive program direction, and health systems planning), being permanent civil servants investigating the ways in which economic interventions can support tobacco control initiatives
- members of health care NGOs and advocacy groups motivating stronger tobacco control interventions

Policy Makers

These individuals formulate, propagate, debate, and legislate policy measures regarding health and/or economic outcomes:

- the national and sub-national Ministers of Health, their advisory staffs, and members of health portfolio committees in the national and sub-national legislatures
- the national and sub-national Ministers of Finance, their advisory staffs, and members of finance portfolio committees in the national and sub-national legislatures
- the national and sub-national Ministers of Labor, their advisory staffs, and members of labor portfolio committees in the national and sub-national legislatures
- the national and sub national Ministry of Agriculture or Industry, their advisory staff, and member of agricultural or industry portfolio committees in the national and sub national legislatures, if the county has a major tobacco agricultural or industrial sector
- other members of the national and sub-national legislatures

Information Requirements of Audience Sub-Groups

Each of the three broad audience sub-groups has their own economic and econometric skills. As a result, each prefers to receive the research findings of the demand analysis in a custom fashion.

Economists

Most economists have a basic academic knowledge of econometrics. While those conducting the actual research are satisfied with a technical explanation of the demand analysis results, the rest prefer to be presented with a combination of:

- an overview of the type, frequency, variables, and quality of the data used
- a concise discussion of the econometric methodology followed, including a brief review of any specification and/or measurement problems encountered and how these were dealt with
- a table of the basic regression results for all specifications of the demand model, including comprehensive diagnostic test results
- a concise discussion of the policy implications of the research results
- an outline of any further economic research questions raised by the findings of the demand analysis which need to be addressed

Other Professionals

Most professionals of the audience have medical or legal backgrounds. Some have a basic working knowledge of statistics (as opposed to econometrics), but few have more than an undergraduate introduction to economics. Consequently, few professionals are satisfied with a technical explanation of the demand analysis results, and most prefer to receive the following:

- a brief listing of the type, frequency, variables, and quality of the data used
- a concise outline of the econometric methodology followed
- a table of the regression results and basic diagnostic tests for the demand specification(s) with the most econometrically significant results
- a table of the estimated elasticities of demand and other basic numerical results, including clear and concise definitions thereof and an appreciation of their degree of precision
- a concise discussion of the policy implications of research results
- a listing of any further economic research questions raised by the findings of the demand analysis which need to be addressed

Policy Makers

Policy makers at all levels are drawn from a wide variety of backgrounds. Except for senior officials from the Ministries of Health and Finance, few have more than an introductory knowledge of statistics, or more than an undergraduate introduction to economics. Policy makers focus much more strongly on the substantive policy implications of the research findings than on the methodology used, as long as they are reasonably assured of the authoritativeness and validity of the research methods. Consequently, policy makers prefer to receive the following information:

- a brief description of the type of data used, together with an assurance that these data are the best available
- a brief description of the econometric methodology followed, together with an assurance that the techniques used are sound and appropriate and that accepted practice is followed in this regard
- a table of the estimated elasticities of demand and other basic numerical results, including clear and concise definitions thereof and an appreciation of their degree of precision
- a concise discussion of the policy implications of research results
- a listing of any further economic research questions raised by the findings of the demand analysis which need to be addressed

Handling Research Results and Policy Implications

Avoid Disseminating Results Separately or Prematurely

The analysis of demand is but one component of a coordinated study of the most important economic aspects of tobacco control in the country concerned. While it is important to communicate the results of the demand analysis as soon as possible to the overall coordinators of the economic study, do not communicate the results more broadly until the results from the other research components (e.g., taxation, smuggling, employment, and equity considerations) are received, collated, and edited into a coherent research report.

It is very important to abide by this point. Consider the following example. The results of a demand analysis suggest that excise tax increases are effective in reducing per capita consumption of tobacco products. Publication of these results is met by the well-rehearsed argument of the tobacco industry lobby that reductions in tobacco product consumption cause:

- job losses in the tobacco growing sector (if the country concerned has one), the tobacco product manufacturing sector (again, if the country concerned has one), and the advertising sector and print media
- loss of government revenue from tobacco excise taxation
- loss of tobacco industry sponsorship of sporting and cultural events
- an unfairly high tax burden on the poor
- increased smuggling of cigarettes into the country

The demand analysis alone cannot produce answers to these issues; instead, input is necessary from the employment, taxation, and equity consideration analyses. Hence it is crucial to coherently present the results of *all* economic analyses to analysts and policy-makers.

Avoid Preemptive Policy Implication Discussions

The depth of coverage of the policy implications of the research results is another important issue to consider. Coverage can differ between the “internal” analysis of demand report and the final “external” economic research report to the coordinators of the tobacco control initiative, the relevant policy makers, and the wider audience interested in tobacco control. It is crucial to maintain a delicate balance: describe and explain the policy implications suggested by the economic research results in sufficient detail to be comprehensive and helpful, but don’t preempt the discretion of tobacco control analysts and policy makers in regard to the actual formulation of policy. The tobacco control analyst’s role is to advise policy makers on the most appropriate interventions, using the research findings of economists and others as critically important inputs in this process.

Structure the Research Reports

The “Internal” Analysis of Demand Report

The report of the analysis of demand is provided to the overall coordinators of the economic study. It is a concise but comprehensive technical briefing on the demand analysis, detailing:

- the type, frequency, variables, sources, and quality of the data used
- concise discussion of the econometric methodology followed
- concise discussion of any specification and/or measurement problems encountered and how these were dealt with
- a table of regression results for all specifications of the demand model, including comprehensive diagnostic test results
- a concise discussion of the policy implications of the research results, together with clear flagging of issues to be referred to or cross-referenced with the other economic analyses
- an outline of any further economic research questions raised by the findings of the demand analysis which need to be addressed

This report forms the basis of the demand analysis component of the Technical Appendix to the "external" report on the overall economic study.

The "External" Report on the Economic Study of Tobacco Control Issues

In the interests of transparency, and to avoid confusion, issue the same research report to all audience sub-groups. In order to meet their different information requirements in the most efficient manner, carefully structure the report with the simplest information appearing first, as follows:

1. An executive summary in bullet-point format, containing:
   - the objectives of the economic study
   - a description of the broad methodological approach applied to each component
   - a brief description of the nature of the data used for the empirical analyses
   - the values and precision of estimates of key demand factors, and a brief description of the policy implications of these findings
   - a listing of any further economic research questions raised by the findings
2. A concise overview of the research, its results, and policy implications, including:
   - the objectives of the economic study
   - a summary of the methodology and results of each analytical component, including:
     - the type and quality of the data used
     - description of qualitative or quantitative methodology used
     - qualitative and/or quantitative results of analysis
   - policy implications of research results from the viewpoint of the study as a whole
   - issues raised for further research
3. A technical appendix containing:
   - a comprehensive listing of the type, frequency, variables, sources, and quality of the data used
   - concise discussion of the econometric methodology followed
   - concise discussion of any specification and/or measurement problems encountered and how these were dealt with

- a table of regression results for all specifications of the demand model, including comprehensive diagnostic test results

Explain Research Results

It is imperative that "external" research reports (and "internal" reports as well, for these are inevitably used as the basis for the external reports) explain the economic research results and their policy implications in simple and compelling terms. To this end, consider the following methods for communicating the concepts involved:

- Spell out implications of demand elasticities in terms of annual per capita consumption, and use examples. Be careful to distinguish between short-run and long-run effects where short-run and long-run elasticities are calculated.
- Graph the consumption data together with the most significant of the independent variables. This demonstrates the potential impact of particular policy instruments more clearly and with greater impact than words.
- Provide an idea of the accuracy of the results (in terms of bias, efficiency, and consistency) and, where necessary, include a sensitivity analysis showing the possible impact of variation in results within the relevant confidence intervals. Spell out in simple terms the implications of estimates being biased *versus* not being efficient, and so on.
- If possible, include a quantitative sensitivity analysis of policy options, explained carefully and simply in text and summarized in table form.

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