EXPECTATIONS FORMATION AND CAPACITY UTILIZATION: EMPIRICAL ANALYSES

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ABSTRACT

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This dissertation consists of three empirical chapters. The first chapter examines the extent to which real-world agents are rational in making quantitative expectations, an issue over which there is much debate. In this chapter dynamic models for new plant-level survey data are estimated in order to test rationality for manufacturing plants that report expectations of capital expenditures. An advantage of such data is that rationality is tested in environments where agents may not have knowledge of each others' expectations, so strategic motives for biases or inefficiencies are minimized. Model estimates and tests suggest that weak implications of rational expectations are rejected, as are adaptive expectations. The second chapter examines expectations formation in the economists' laboratory as psychologists have documented several biases and heuristics that describe deviations from Bayesian updating-a standard assumption for economists. Indeed, Confirmation Bias predicts that individuals will exhibit systematic errors in updating their beliefs about the state of the world given a stream of information. This chapter examines this bias within a non-strategic environment that motivates experimental subjects financially to provide probability estimates that are close to those of a Bayesian. Subjects revise their estimates of the state of the world as they receive signals. Comparing their estimates to those of a Bayesian shows that subjects display conservatism by underweighting new information. In addition, subjects display confirmation

bias by differentiating between confirming and disconfirming evidence. The third chapter seeks to determine, through reduced-form Phillips curves estimates and a structural model, whether the indicator relationship between capacity utilization and inflation has diminished as in recent years high levels of capacity utilization have not led to higher inflation. In Canada, the capacity utilization rate is benchmarked to survey data, thereby providing a unique opportunity to empirically analyze this macroeconomic relationship. Estimates of time-varying parameters and structural break models indicate that there have been breaks over time in the relationship. The timings of the breaks suggest that increasing competitiveness and a rules-based monetary policy may help account for the demise of the relationship. Estimates of a monopolistically competitive sticky-price model economy qualitatively lend credence to this conjecture.

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PREFACE

This dissertation is composed of three chapters that reflect my academic interests in applied macroeconomics and experimental/behavioral economics. In this preface I would like to acknowledge and thank those individuals who were instrumental in the development of these interests and in guiding this dissertation to completion.

Professors John Duffy, Roberto Weber and Lise Vesterlund provided much guidance and many insightful comments that I hope I have successfully incorporated in this dissertation. Indeed what I know of experimental economics, in particular as it applies to macroeconomics, is in large part due to their influence.

I also owe many thanks to Professor Jean-Francois Richard. What I know of applied econometrics and modeling is a direct result of his teaching, research and guidance. Professor Richard been fundamental in my development as an economist and I hope that in the years to come my own research can live up to his standard of intuitive and technical sophistication.

The second chapter of this dissertation is joint work with Katherine Willey Wolfe. Indeed, her contributions converted a rough first idea into the chapter presented below; a conversion that would never have happened without her deep understanding and experience in the discipline. I look forward eagerly to reading her future research and continuing our collaboration, which I must admit leaves me with the larger share of the total benefit.

The interests that I developed in behavioral economics are a direct result of the involvement of Rahma Abdulkadir. Through extensive discussion she convinced me of the importance of psychological aspects of economic decision-making and thus introduced me to the field of psychology and economics. In addition, her unwavering support and encour-

agement in all matters has led to the completion of this dissertation despite a number of obstacles. Indeed any confidence I have in pursuing an academic career is derived entirely from her encouragement and belief. I can only hope that I may be as instrumental, in as varied a manner, in her graduate career as she has been in mine.

The importance of the dissertation supervisor in the development of a thesis can never be understated. It suffices to say that every section of every chapter in this dissertation has benefited significantly from the supervision and advice of Professor David N. DeJong. In addition, his involvement and influence in my education and professional development has been as important as the guidance he gave to this dissertation. At the very least, I have learnt the process of research, teaching and all that is required in being an accomplished academic by watching his example. It is my hope that I can acknowledge his guidance and teaching inputs into any development I may have undergone, by my career output. If the quality of that output can exceed his expectations and demonstrate to him that regardless of the material presented in this document, I have done better, then no peer-review I may receive will be more valued.

In summary, I take sole responsibility for the shortcomings of this dissertation and attribute to those acknowledged above, any contributions the contents of this dissertation might make to the discipline.

This dissertation is dedicated to my parents, Shri Vardhan & Mira Pande, and grandparents: Krishna Kanath & Malti Dave and Madhu Sudhan & Kamla Yagnik.

1.0 ARE INVESTMENT EXPECTATIONS ADAPTIVE, RATIONAL OR NEITHER?

1.1 INTRODUCTION

Theories of expectations formation have been central to the macroeconomic literature for as long as the field has been attempting to generate business cycles in stochastic environments. Since the introduction of Muth's (1961) concept of the Rational Expectations Hypothesis (REH), the theory of rational expectations has been predominant in theoretical models of the aggregate economy. However, the hypothesis has been debated as researchers, who have looked to field and experimental data, have found ambiguous results. This chapter adds to the debate by examining new field data for manufacturing plants who form a central modeling object of business cycle theories.

Field-data exercises have focused on data drawn from a small class of professional forecasters and generally face difficulties at two levels: the form of available data and subsequent econometric modeling. At the data level the main issue is the representativeness of estimates drawn from the activities of professional forecasters. At the econometric level the main issues relate to the estimation constraints imposed by individuals forming expectations or forecasts on the same public variable. In general, inferences have been mixed with some researchers finding rationality to hold[1] and others finding that when the econometric issues raised by pooled forecasts are addressed, rationality tests fail[2]. In short, the debate is ongoing and cer-

[1] See Keane & Runkle (1990, 1998).
[2] See Bonham & Cohen (2001).

tainly inconclusive. This chapter adds to the discussion by providing inferences from a large class of agents, who form quantitative expectations on the variable of capital expenditures on machinery and equipment. The nature of the data allows not only for inference for a large economic sector but for agents who form private expectations. Therefore the aforementioned concerns are addressed and the debate over rationality is enthused by analysis of rich and relevant data.

Given this motivation for testing the REH outside of financial markets, Section 1.4 provides econometric evidence, having discussed the plant-level data in Section 1.2 and the models in Section 1.3. Section 1.5 concludes and summarizes the main results of the analysis conducted: estimates of the standard rationality equations from the literature indicate that rationality cannot be inferred. Using appropriate estimators it is clear that investment expectations are neither adaptive nor rational. This result is not new for qualitative-response data as, for example, Das & van Soest (2000) have found similar results when examining household income expectations. Here the evidence is stronger for two reasons. First, the data are for a variable for which private forecasts are made, thereby reducing biases induced by strategic motives. Second, the tests conducted are for weak implications of rationality. A strong test of rationality would test an economic model jointly with the expectations formation process. However, tests only of the expectations formation process are carried out, therefore rejection of these weak tests is quite a strong result. The remainder of this section elaborates on some recent related studies and defends the validity of these weak tests.

1.1.1 RELATED LITERATURE

Recent studies have focused on data drawn for professional forecasters who are typically active in financial markets. In financial markets it seems reasonable to assume that agents do follow the dictates of rational expectations, in that they do not make predictable forecast errors without due cause. Public observability of the decisions of market participants, such as professional forecasters, can further induce a lack of observed forecastable errors. The majority of the literature tests the REH in the form of forecast rationality, as distinct from the implicit Bayesian updating procedure that generates such behavior. In particular, a large literature in behavioral finance had noted that financial analysts may over (under) react to information in a pattern inconsistent with the predictions of the REH[3]. Such results were largely based on least-squares regressions of realizations on forecasts of a variety of variables. However, these studies had neglected to model the information sets of professional forecasters, implying that the least-squares techniques were biased towards rejecting the REH or falsely accepting it. Keane & Runkle (1990, 1998) recognized the nature of the cross-correlations inherent in forecast errors, arising from plausible assumptions on the information shared by forecasters, the timeline of the data and other data properties. Using generalized method of moments techniques they incorporated these data properties and then tested the REH, with the result that forecast rationality held.

In a recent analysis, Bonham & Cohen (2001) further investigate the econometric foundations of the tests conducted by Keane & Runkle (1990). In particular, their concern is with testing rationality using either consensus (that is, averaged) or pooled cross-section time series versions of the professional forecaster survey data. They argue that since the target time series being forecasted by individuals in the Survey of Professional Forecasters are often integrated, individual rationality regressions must share the same coefficients across forecasters. That is, following Zellner (1962), microhomogenaity must exist. They then show that this microhomogenaity is crucial for tests of rationality using either consensus or pooled data. Their microhomogenaity test results indicate that it is not necessarily a tenable hypothesis and they conclude,

> "Since individual rational expectations imply microhomogenaity in the panel, rejection of microhomogenaity implies some degree of bias in panel forecasts."

Therefore the debate over rationality is certainly not resolved even when it centers on professional forecasters.

It is important to note that this entire line of research, from Zarnowitz (1985) to Bonham & Cohen (2001), is on testing the rationality of agents who together forecast the same

[3] An analysis and a review of the behavioral heuristics that may be at work in financial markets is provided by Barberis et. al. (1998).

public variable. The panel data employed in this chapter are fundamentally different from those employed in such studies as they are for agents who report expectations of the same private variable. Also, whereas these and other financial market studies concentrated on agents whose forecasts and realizations were clearly observable to one another, the data collected on manufacturing plants in this chapter are not of that form. Therefore cross-correlations in forecast errors implied by what each forecaster knows about another are not relevant for the data used below. This provides justification for the use of standard panel data econometric techniques. However, these expectations are 'real' in the sense that the agent has an economic incentive to form and report them. The data are for manufacturing plants from Statistics Canada's Capital Expenditures Survey (Actual and Forecast) that requests information businesses already have on hand for internal decision making processes. Therefore the derivation of the relevant estimating equations is different from that currently present in the literature. In particular these data are not 'off the cuff' forecasts but well-thought-out business plans. Thus, given the relevance of manufacturers' expectations of capital expenditures, the remaining issues relate to the specification of the reduced form equations.

1.1.2 SPECIFICATION ISSUES

Presumably, capital expenditures are incurred in order to achieve some optimal level of capital stocks given adjustment costs. In formulating, say, a partial adjustment model of capital stock, a strong test of rationality is a joint test of the economic model as well as the expectations formation mechanism. However, given that capital stock data are not available, weak tests are carried out.

This leaves two particular considerations. The data are annual and so did not exhibit large jumps in capital expenditures vis-a-vis output at the plant level, therefore a threshold switching model implied by fixed costs of adjustment is not relevant. Whereas one can imagine such threshold effects as examined by Hamermesh (1989, 1992) holding in high frequency micro data on capital expenditures, the data used in this chapter are not of that form. Plots for each plant (across time), of shipments and realized capital expenditures, showed that capital expenditures fluctuated with output. Were the level of such expenditures relatively constant across time except in episodes of large changes in shipments, threshold effects of capital expenditure plans changes would be relevant. However, thresholds with respect to size variation are a possibility and are addressed in the specifications estimated.

Finally, if the true data generating process is being driven by say, gradual adjustment, then clearly capital expenditures will reflect that fact. Thus, models are estimated that look for weaker versions of forecast rationality, by limiting the information set with respect to which orthogonality is sought.

1.2 THE DATA

Data were compiled from two surveys: the Capital Expenditures Survey (CES) produced by the Investment and Capital Stock Division of Statistics Canada and the Annual Survey of Manufactures (ASM) produced by the Manufacturing, Construction and Energy Division of Statistics Canada. The former yielded data on capital expenditures and the latter on shipments. Both surveys also provided categorical variables that were employed in creating the panel dataset. The focus in this chapter is on the manufacturing classification and as a result only records matching this industry were chosen for analysis[4].

This section describes the sampling methods employed by the surveys, the variables collected for analysis and the results of matching the surveys across time. The objective was to obtain a panel that tracked manufacturing plants in operation over time, as defined by the administrative variables available from the surveys.

1.2.1 SAMPLING METHODS AND SURVEY TIMING

The CES has distinct phases for each yearly sample. The first relevant phase is the 'Actual Survey' that requests information on capital and repair (including maintenance costs)

[4] The data for both surveys are proprietary to Statistics Canada.

expenditures on construction and machinery & equipment for a fiscal year ended (in calendar year t). This survey is mailed out in March of calendar year $t+1$ so that the data are procured after a firm's fiscal year has ended. The next relevant phase is the 'Preliminary Survey' that requests the same information as the Actual Survey, except that it also has a expectations component. That is, businesses are asked to report their expectations for capital expenditures for an upcoming fiscal year (that will end in calendar year t). This survey is mailed out in October of calendar year $t-1$; the timing of the phases is important as it reflects what sort of information businesses have when making their expectations. Figure 1 in Appendix C presents the stages of the CES, and as can be seen by the timing represented there is some overlap between the two phases. However, by the time businesses report expectations for the upcoming period, their fiscal year is well over implying that the two phases are rough approximations to one step ahead expectations. Finally, firms have an incentive to report their expectations as the editing procedure for the CES involves contacting respondents repeatedly to ensure data quality. If reported data seem amiss with respect to the respondents' past reports and values from various financial statements, then the respondent is contacted and the discrepancy is resolved.

For the available data, for every calendar year, samples of businesses are drawn from a stratified concept of a population which represents the universe for inclusion in the CES and ASM. Each survey draws a sample (based on industries and geographic regions) independently based on the income statement variable of gross business income. The ASM is conducted once a year and requests information on input expenditures and output shipments for the fiscal year just ended. In addition this general sampling method relies on certain identifiers that correspond to different concepts of a measurement unit. The ASM uses an identifier termed the Record Serial Number (RSN), and the CES uses the Universal Identifier (UID). The RSN is a finer identifier in that it considers industries and a finer level of geographic classification, in contrast the UID is broader. Consequently, several RSNs' match to a single UID and since the only identifier that was available across surveys was the UID, it was the one used to match the cross sections across time.

An important consideration in the panel data creation is temporal constancy of the sampling methods. The CES samples were generally static (except for occasional correction for births and deaths) until 1992, they became dynamic with heavy rotation of businesses in later years. This was witnessed by dramatic decreases in match rates starting in 1993. Since the loss of units was not due to business failure but a change in the nature of the survey methods (both in terms of sampling and the concept of an observational unit), the panel was created for the years 1986-1992.

1.2.2 VARIABLES

The CES provided data on actual purchases of capital machinery and repairs expenditures (x_{it}) and expected purchases of capital machinery and repairs expenditures (y_{it}) for $j \in J$ plants. Construction expenditures were not considered since what was required was a variable on which one step ahead expectations are reasonable. Given the lumpy nature of construction investment, construction capital expenditures would not fit that category well. The CES also provided categorical variables that pertained to whether the unit was deemed to be in business or not, if it had been amalgamated into another identifier etc. In effect units that matched the concept of a manufacturing plant were kept as long as they remained operational as defined by Statistics Canada. The ASM provided data on the value of manufacturing shipments (z_{it}), an output measure used to compute gross domestic product at factor cost, and categorical variables used to adhere as closely as possible to the concept of a manufacturing establishment or plant. In summary three variables (in addition to categorical variables) were taken from the CES, and one from the ASM. Further, tabulation of the number of units falling under various two digit industry classes indicated that these categories were well represented.

1.2.3 THE SURVEY QUESTION AND DATA PROPERTIES

It is important to note the exact question units are answering when responding to the surveys. In the Actual CES they are asked to report their expenditures on new capital machinery and repairs (financial statement variables), in the expectations phase they are asked to,

> "...report the [capital expenditures on new machinery and repairs] expected to be put in place during the [fiscal] year."

Figures 2-29 in Appendix C present the data for each cross section from 1986 through 1992. Figures 2-15 plot expectations versus realizations as well as the 45-degree line. These figures show that there is significant mass at the lower end of the distribution and significant dispersion throughout the years. The plants at the lower end were further analyzed for any behavior that was qualitatively different, the only distinguishing characteristic was a fair amount of dispersion[5]. Figures 16-29 provide plots of the expectations error ($\varepsilon_{it} = x_{it} - y_{it}$) versus individuals in each cross section. There seems to be a fair amount of dispersion here as well. Further, both sets of figures indicate linear relationships. Table 1 in Appendix B provides the summary statistics for the panel as a whole and confirms the dispersion noted in the plots[6].

Tables 2 and 3 in Appendix B provide the yearly sample correlations. These correlations indicate that expectations and realizations are highly correlated, however the correlation between past realizations and expectations errors is also high, indicating a certain degree of persistence. In summary, despite the strong linear relationships shown in Figures 2-29, there is strong motivation to test the REH given that the aggregate data and sample correlations indicate a degree of persistence. The main data features to incorporate in the econometric models are unobserved individual and time variation due to the dispersion and possible temporal shifts in the data. The next section provides dynamic models for

[5] In Figures 2-29 there are two plots for each year. In the first plot all of the data are provided, in the second, data are plotted for the lower end of the distribution.

[6] In the table, for a variable v_{it}, the transformations reported are the following: 'Overall' is $\overline{\overline{v}}$ where the mean is taken over time and individuals. 'Between' is $\overline{v}_i$ where the mean is taken over time only. 'Within' is $v_{it} - \overline{v}_i + \overline{\overline{v}}$.

several expectations formation mechanisms as derived from the two central theories used in macroeconomic theories: the adaptive and rational expectations hypotheses.

1.3 MODELS OF EXPECTATIONS FORMATION MECHANISMS

This section provides testable models of various expectations formation mechanisms having discussed the main estimation method. Tests of the AEH are provided first followed by tests of the REH and a general Expectations Efficiency Hypothesis (EEH).

1.3.1 ESTIMATION METHOD

Many of the reduced form models in this chapter will take the form of dynamic random effects panel models. In such a formulation least-squares estimates are inconsistent and biased upwards due to the inclusion of lagged dependent variates (even if the errors are uncorrelated). Further, for the same reason, within-groups estimates are biased downwards and are consistent in only large T asymptotics[7]. In light of these issues Anderson & Hsiao (1981) proposed an instrumental-variables estimator; however it is not efficient when $T > 3$ as is the case for the data in hand. As a result Arellano & Bond (1991) proposed a generalized method of moments (GMM) estimator that first-differences the dynamic equation, and uses lagged variates as instruments in order to obtain efficient estimates.

However, this standard GMM estimator has been shown to suffer from considerable finite-sample bias and relatively poor precision in simulations, especially in cases where the parameter on the lagged dependant variate tends to one. Given the undesirable characteristics of the standard GMM estimator, the literature has looked towards imposing additional assumptions on the dynamic panel in order to improve the performance of the estimates. Of the several studies, Blundell and Bond's (1998) restrictions on the initial conditions are considered relatively mild, and their 'system GMM' estimator has been shown to outperform

[7] See Baltagi (2001, Chapter 8) for details.

the standard GMM estimator both in simulations and with live data[8]. The restrictions employed by Blundell & Bond (1998) arise from the additional assumptions that Δy_{it}, Δx_{it} and Δz_{it} are uncorrelated with the unobserved random effects and that the processes are mean stationary. These assumptions are reasonable for the data at hand, especially given the fact that the manufacturing plants have been in operation for a fairly long time. Therefore the Blundell & Bond (1998) estimator is employed in estimating dynamic panels[9].

1.3.2 THE ADAPTIVE EXPECTATIONS HYPOTHESIS

The general theory of extrapolative expectations provides the following specification for the relationship between expectations (y_{it}) and realizations (x_{it}),

$$y_{it} = \sum_{j=0}^{\infty} w_j x_{it-1-j} \tag{1.1}$$

The theory of Adaptive Expectations as stated by Keynes (1936) and interpreted by Hicks (1939) (as cited by Lovell (1986)) adds the following to (1.1),

$$w_j = \beta(1-\beta)^j, \qquad \beta \in [0,1] \tag{1.2}$$

In which case, as Nerlove (1983) presents,

$$y_{it} - y_{it-1} = \beta(x_{it-1} - y_{it-1}) \tag{1.3}$$

The model in (1.3) is a restricted specification, therefore the unrestricted version is to be estimated and the restriction tested. To do so, rewrite (1.3) as follows,

$$y_{it} = \alpha_0 + \alpha_1 y_{it-1} + \alpha_3 x_{it-1} + \upsilon_i + \lambda_t + \xi_{it} \tag{1.4}$$

[8] See Blundell, Bond & Windmeijer (2000) for a complete review of the issues in dynamic panel estimation.

[9] The Blundell & Bond (1998) estimator expands upon that of Arellano & Bover (1995), who were the first to suggest a systems approach. Both estimators were employed, with little difference in the estimates. The Blundell & Bond (1998) estimates are reported as their estimator performs well even when instruments may be weak.

with the test for Adaptive Expectations being whether the following restriction holds,

$$H_0 : \alpha_1 + \alpha_3 = 1 \tag{1.5}$$

where $\alpha_3 = \beta$. The empirical specification in (1.4) contains unobserved individual variation (υ_i), unobserved time variation (λ_t) and an idiosyncratic error (ξ_{it}). Thus the specification takes the form of a random effects dynamic panel. The assumptions placed on the random effects and the idiosyncratic error are,

$$E(\upsilon_i) = 0,\ E(\upsilon_i \xi_{it}) = 0,\ E(\xi_{it}) = 0 \tag{1.6}$$

In addition, if the model is correct then the following should hold,

$$E(\xi_{it}\xi_{is}) = 0 \quad \forall\ t \neq s \tag{1.7}$$

The standard moment conditions are $E(y_{it-s}\Delta u_{it}) = 0$ for all $t \geq 3$ and for all $s \in [2, t-1]$ and $E(\Delta y_{it-1}u_{it}) = 0$ for all $t \geq 3$ where $u_{it} = \upsilon_i + \xi_{it}$. The remaining requirement of the Blundell & Bond (1998) approach requires specification of the relationship between the independent covariates and the error (ξ_{it}). Given that the entire information set is unaccounted for, and assuming adaptive behavior, a natural assumption is that x_{it-1} and ξ_{it} should be correlated but x_{it} and ξ_{it+1} should not. This implies that in addition to the moment conditions outlined above the following are also available, $E(x_{it-s}\Delta u_{it}) = 0$ for all $t \geq 3$ and for all $s \in [2, t-1]$.

1.3.3 THE RATIONAL EXPECTATIONS HYPOTHESIS AND EEH

Rational expectations, in the sense of Muth (1961), has led to two (related) methods prevalent in macroeconomic model building. The first, termed the REH, replaces one-step-ahead expectations of variables with realizations and an error. The second, termed the EEH, treats expectational errors as being orthogonal to past information; the two hypotheses are clearly related and therefore suggest the two tests of rationality provided below. The first test is the standard in the literature where the Muth (1961) condition is directly estimated and tested. The second test postulates a dynamic model of computed expectational errors and tests for any persistence.

1.3.3.1 THE REH The theory of Rational Expectations entails specifying the relationship between expectations and realizations as,

$$y_{it} = E(x_{it} \mid \Omega_{it-1}) \tag{1.8}$$

where $\Omega_{it-1} = \{\cdots, y_{it-1}; \cdots, x_{it-1}; \cdots, z_{it-1}\}$ is the set of information available to the plants under consideration here. In order to convert the above relationship into a testable regression specification, assuming that expectations and realizations are related linearly, Muth (1961) requires first that the expectational error be distributed independently of expectations. The requirement of lack of a correlation between the error and expectations implies a non-zero correlation of the errors with realizations. Further, Muth (1961) also requires that errors be uncorrelated with any element of an agents' information set in order for the agent to be referred to as fully rational[10]. These requirements, given the timing of the survey data, translate into the following regression model,

$$x_{it} = \alpha_0 + \alpha_1 x_{it-1} + \alpha_2 y_{it} + \alpha_3 y_{it-1} + \alpha_4 z_{it-1} + \upsilon_i + \lambda_t + \xi_{it} \tag{1.9}$$

The test for fully rational expectations is,

$$H_0 : \alpha_1 = 0; \alpha_3 = 0; \alpha_4 = 0; \alpha_2 = 1 \tag{1.10}$$

In order to complete the specification, assumptions (1.6) and (1.7) above are adopted. The standard moment conditions are $E(x_{it-s}\Delta u_{it}) = 0$ for all $t \geq 3$ and for all $s \in [2, t-1]$ and $E(\Delta x_{it-1} u_{it}) = 0$ for all $t \geq 3$ where $u_{it} = \upsilon_i + \xi_{it}$. The only remaining requirement is specification of the relationship between the independent covariates and the error (ξ_{it}). Let X_{it} denote the matrix containing y_{it}, y_{it-1} and $z_{it-1,}$ then in order to complete the model specification the relationship between X_{it} and ξ_{it} needs to be specified under the null of rationality. Rationality would by itself imply that the regression error (ξ_{it}) be uncorrelated with X_{is} for all s and t. However, given that the entire information set is unaccounted for, a more reasonable assumption is a lack of contemporaneous correlation and correlation with all past errors. This implies that in addition to the moment conditions outlined above the following are also available, $E(X_{it-s}\Delta u_{it}) = 0$ for all $t \geq 3$ and for all $s \in [1, t-1]$.

[10] See Lovell (1986).

1.3.3.2 THE EEH The REH implies that expectational errors are unsystematic and orthogonal to lagged information, denoted the EEH[11]. In order to test this version of the hypothesis define,

$$\varepsilon_{it} = x_{it} - y_{it} \tag{1.11}$$

Then rationality requires,

$$E(\varepsilon_{it} \mid \Omega_{it-1}) = 0 \tag{1.12}$$

where $\Omega_{it-1} = \{\cdots, \varepsilon_{it-1}; \cdots, z_{it-1}\}$ is the information set and is assumed to be linearly related to the expectational error. In order to translate the above relationship into a testable regression specification for rationality, Muth (1961) requires that the error be uncorrelated with elements of the information set. The elements in the context of the present analysis are the lagged error and lagged shipments. Thus rationality requires that in the following regression,

$$\varepsilon_{it} = \alpha_0 + \alpha_1 \varepsilon_{it-1} + \alpha_4 z_{it-1} + \upsilon_i + \lambda_t + \xi_{it} \tag{1.13}$$

the overall regression error be uncorrelated with known information motivating the following test of this EEH hypothesis,

$$H_0 : \alpha_1 = 0; \alpha_4 = 0 \tag{1.14}$$

Specification (1.13) is also a dynamic panel model and the previous comments and assumptions regarding the error and random effects apply. The standard moment conditions are $E(\varepsilon_{it-s}\Delta u_{it}) = 0$ for all $t \geq 3$ and $s \in [2, t-1]$ and $E(\Delta\varepsilon_{it-1} u_{it}) = 0$ for all $t \geq 3$ where $u_{it} = \upsilon_i + \xi_{it}$. In order to complete the model specification the relationship between z_{it-1} and ξ_{it} needs to be specified under the null of rationality. Rationality would by itself imply that the regression error (ξ_{it}) be uncorrelated with z_{is} for all s and t. However, given that the entire information set is unaccounted for a more reasonable assumption is a lack of contemporaneous correlation, and correlation with all past errors. This implies that in addition

[11] This particular test is similar to one for adaptive expectations, however, this specification imposes no relation such as that in (1.2). Indeed the EEH test will reflect a degree of adaptive expectations if the data are persistent and there is remaining residual autocovariance. The distinction allows the determination of the degree of persistence and can account for size variation.

to the standard moment conditions for this dynamic panel the following are also available, $E(z_{it-s}\Delta u_{it}) = 0$ for all $t \geq 3$ and for all $s \in [1, t-1]$.

1.3.3.3 THE EEH AND SIZE VARIATION Next, given that there is significant dispersion in the data, the model in (1.13) must be conditioned on the fact that an error made by a small plant is fundamentally different than that by a large plant. For example, if a large plant makes an error of $1 million but has revenues and investment expenditures in the hundreds of millions the error is of less consequence than if a small plant who might make an error of $10,000 and have investment expenditures of $100,000. In order to incorporate this feature, (1.13) may be rewritten by redefining the error as,

$$\epsilon_{it} = \frac{x_{it} - y_{it}}{y_{it}} \tag{1.15}$$

and similarly writing $z'_{it} = \frac{z_{it}}{y_{it}}$ yielding the following model,

$$\epsilon_{it} = \alpha_0 + \alpha_1 \epsilon_{it-1} + \alpha_4 z'_{it-1} + \upsilon_i + \lambda_t + \xi_{it} \tag{1.16}$$

Now the test of rationality is whether there is any persistence in errors as a fraction of expectations.

$$H_0 : \alpha_1 = 0; \alpha_4 = 0 \tag{1.17}$$

Specification (1.16) is also a dynamic panel model and the previous comments and assumptions regarding the error and random effects apply. The standard moment conditions are $E(\epsilon_{it-s}\Delta u_{it}) = 0$ for all $t \geq 3$ and $s \in [2, t-1]$ and $E(\Delta\epsilon_{it-1}u_{it}) = 0$ for all $t \geq 3$ where $u_{it} = \upsilon_i + \xi_{it}$. In order to complete the model specification the relationship between z'_{it-1} and ξ_{it} needs to be specified under the null of rationality. Rationality would by itself imply that the regression error (ξ_{it}) be uncorrelated with z'_{is} for all s and t. However, given that the entire information set is unaccounted for a more reasonable assumption is a lack of contemporaneous correlation, and correlation with all past errors. This implies that in addition to the standard moment conditions for this dynamic panel the following are also available, $E(z'_{it-s}\Delta u_{it}) = 0$ for all $t \geq 3$ and for all $s \in [1, t-1]$.

Finally it is important to note that nowhere in the hypothesis tests above is the constant required to equal zero. Strictly speaking the constants should equal zero across the specifications. However, in order to allow unobserved heterogeneity to consist of variation common to all plants and through time, so as to account for any asymmetries in the costs of errors, this requirement is not imposed.

1.4 ESTIMATION RESULTS

1.4.1 ESTIMATION RESULTS I

Table 4 in Appendix B provides the estimation results for equations (1.4)-(1.16)[12]. For each equation the least-squares, within-groups and system GMM estimates are provided. In order to ensure the validity of the instruments, Sargans' test is provided in addition to tests for autocovariance in the residuals. For each null, the F-statistic is provided in Table 5. In evaluating the estimates two items are of interest. First the estimate of the lagged dependent variable should lie between the OLS and Within estimates; second, the within transformation wipes out the constant in estimation and so its' estimate is not provided.

The GMM estimates for equation (1.4) clearly imply a rejection of the null of the AEH. The fit is good and there does not seem to be any autocovariance in the errors; further, the overidentifying restrictions are accepted. The GMM estimates for equation (1.9) clearly demonstrate the precision that is gained with the system GMM estimator, however rationality is rejected. Here the maintained hypotheses of no autocovariance is rejected and the overidentifying assumptions are not rejected. It is important to note that the GMM estimate for α_2 is closer to the overall correlation between y_{it} and x_{it} from Table 3. The desirable features of the estimates of equation (1.9) are that z_{it-1} enters with a virtual zero coefficient; however, there is much persistence in that the coefficient on lagged expectations is strong.

[12] In the table, robust standard errors are in parentheses and time dummies included in the estimation. The Within transformation removes the constant from the specification and so is not reported. The m_1 and m_2 test statistics are for tests of autocovariance of orders 1 and 2 respectively. The S test statistic is the Sargan test for overidentifying restrictions.

The estimates for equations (1.13) and (1.16) do not fare better in testing for rationality, there is clearly persistence in the errors and even accounting for size variation does not imply rationality. The results also suggest that there is some residual autocorrelation as the test statistics for these hypotheses are low. Overall, the estimates suggest a fair amount of persistence in expectations errors.

In addition, the autocovariance and Sargan tests for most of the equations imply that the maintained assumptions in estimation are upheld. The important feature of the results in Table 4 is that the correlations in Tables 2 and 3 are approximated by the GMM estimates thereby strengthening the inferences that can be drawn. Overall, the AEH, REH and EEH tests are rejected.

1.4.2 ESTIMATION RESULTS II

The estimation results above suggest that the AEH does not hold, expectational errors exhibit persistence and a one-to-one relationship between expectations and realizations is doubtful. In order to solidify these results it is necessary to estimate a weaker model for the AEH, estimate the implied model for (1.9), and to test both in order to verify the failure of the AEH and the implied rational expectations model for the data.

Turning first to the unrestricted AEH model in (1.3), let $\Delta y_{it} = y_{it} - y_{it-1}$, expand the right hand side and consider the following specification,

$$\begin{aligned}\Delta y_{it} &= \alpha_0 + \alpha_1 y_{it-1} + \alpha_3 x_{it-1} + \upsilon_i + \lambda_t + \xi_{it} \\ \xi_{it} &= \rho \xi_{it-1} + \phi_{it} \\ |\rho| &< 1,\ \ \phi_{it} \sim iid(0, \sigma_\phi^2)\end{aligned} \tag{1.18}$$

with the test,

$$H_0 : \alpha_1 + \alpha_3 = 0 \tag{1.19}$$

In this specification the errors are allowed to be autocorrelated, and as the specification is not dynamic, Baltagi & Wu's (1999) random effects GLS estimator can be employed. If the null fails, then there is definitive evidence against the AEH, as then both the restricted and unrestricted models' null hypotheses ((1.5) and (1.19)) fail.

Next, the results from the previous section suggest persistence in errors and possible non-orthogonality of the errors with information that should have been known. Further, the estimation results suggest that the problem lies not in the estimates for the z_{it-1} coefficients but for lagged expectations and realizations. Therefore consider the following model,

$$\begin{aligned} x_{it} &= \alpha_0 + \alpha_2 y_{it} + \alpha_3 y_{it-1} + \upsilon_i + \lambda_t + \xi_{it} \\ \xi_{it} &= \rho \xi_{it-1} + \phi_{it} \\ |\rho| &< 1,\ \phi_{it} \sim iid(0, \sigma^2_\phi) \end{aligned} \tag{1.20}$$

with the test,

$$H_0 : \alpha_2 = 1; \alpha_3 = 0 \tag{1.21}$$

Finally, in order to verify the extent to which the coefficient on x_{it} is less than one, while allowing for autocorrelated errors, consider,

$$\begin{aligned} x_{it} &= \alpha_0 + \alpha_2 y_{it} + \upsilon_i + \lambda_t + \xi_{it} \\ \xi_{it} &= \rho \xi_{it-1} + \phi_{it} \\ |\rho| &< 1,\ \phi_{it} \sim iid(0, \sigma^2_\phi) \end{aligned} \tag{1.22}$$

with the test,

$$H_0 : \alpha_2 = 1 \tag{1.23}$$

Specifications (1.20) and (1.22) are weaker forms of rationality as there may be information that plants utilized to form expectations that is unobserved; the exclusion of the lagged dependent variable should allow for some flexibility. The estimates of these specifications are provided in Table 6 of Appendix B[13].

[13]Note that in the table the $B - W$ tests reports the Baltagi & Wu (1999) locally best invariant test statistic for the null that $\rho = 0$. Time dummies were included in the estimation and standard errors are robust.

The estimates for (1.18) clearly demonstrate that the AEH is rejected. Further, the fit seems to be rather weak and the Baltagi & Wu (1999) $(B-W)$ test statistic rejects that $\rho = 0$. The estimates for (1.20) indicate that $\rho \neq 0$ and that lagged realizations enter positively. Rationality is clearly rejected as it is in the estimates for (1.22) as well. An important feature of these latter estimates is that the estimate for α_2 is similar to that of the GMM estimate of equation (1.9) in the above section, however, there is considerable persistence in the data and rationality cannot be accepted.

1.4.3 ESTIMATION RESULTS III

The estimation results presented so far indicate that the data do not seem to match the various rationality hypotheses considered. There may be additional explanations for why these tests are being rejected, as discussed in Section 1.1.2. The first is that plants may have multi-year plans, rendering the lagged variables with significantly non-zero coefficients. The second is that variation across size is not being appropriately measured, indeed it would be useful to have a dollar figure above which plants are 'more rational' than those falling below a certain threshold.

In order to address these concerns the ideal method would be to estimate a random effects dynamic panel model with thresholds. Here the endogenously estimated threshold would reflect size variation. However, since it is difficult to obtain consistency of such estimators (Hansen (1999)) an alternative approach is to stack the data, assume away random effects and estimate a threshold model without the lagged variables. For this purpose the methods of Hansen (2000) are applicable. The method is devised for estimating linear relationships under thresholds, where the threshold is estimated endogenously. The model under consideration is,

$$\mathbf{x}_t = \left\{ \begin{array}{ll} \beta_{10} + \beta_{11}\mathbf{y}_t + \phi_t & \forall \mathbf{q}_t > \widetilde{\mathbf{q}} \\ \beta_{20} + \beta_{21}\mathbf{y}_t + \phi_t & \forall \mathbf{q}_t < \widetilde{\mathbf{q}} \end{array} \right\} \tag{1.24}$$

where the variates in bold represent data that have been stacked across individuals and $\mathbf{q}$ is a threshold variable. The above model was estimated with the threshold being shipments $(\mathbf{z}_t)$

using Hansen (2000)'s method under heteroscedastic disturbances. The estimation results are presented in Table 7 of Appendix B. The table indicates that above a threshold of $104 million in shipments, plants are 'more rational' in that they are closer to a slope estimate of one, those below the threshold clearly fair worse.

Finally, the same model was also estimated with the absolute forecast error as the threshold variable, estimates are presented in Table 7 as well. The estimates confirm a standard intuition: those who make small errors are 'more rational' than those who do not. The interesting results from both of these sets of estimates is that they are for plants who have been in business for a long period of time.

1.5 CONCLUSION

The debate over the extent of rationality of market participants can be joined when expectations formation mechanisms are tested with rich and relevant data. Such an exercise has been carried out in this chapter with strong results. It is important to note that the results of this chapter have no consequences for the general Lucas critique; rather they indicate that the statistical formulation of rationality in terms of Muth's (1961) condition does not hold. In particular weak implications of rational expectations are tested and rejected.

A general conclusion of this chapter is that evidence from micro data can be crucial in developing stylized facts for business cycle models. Here, tests have been provided that clearly reject adaptive and rational expectations in their traditional forms. These results are obtained for a large class of economic agents observed for a long time period (seven years). Further, investment is a decision variable for which a clear expectations test can be conducted and the results are strong both in terms of the parameter estimates and hypothesis tests. Indeed in an earlier version of this chapter the standard first-difference estimator was employed. The results indicated a rejection of adaptive expectations and full rationality (equations (1.4), (1.9) and (1.13)). However, the hypothesis test for equation (1.16) was not rejected suggesting rationality in so far as plants are able to afford it. As the standard first-difference estimator suffers from bias in finite samples and lacks precision, the results are stronger with the system GMM estimator employed here. Therefore even the behavioral hypothesis that plants are rational in so far as they balance the costs and benefits of updating is doubtful, even when testing only a weaker version of rationality.

Finally, there are several studies that have found that agents either over-or-under estimate both in field and experimental data. This is not a new fact. However, the finding for such a large class of agents is important for macroeconomic models, which aim to be consistent with micro data. Consistency with micro data using appropriate estimation techniques should, after all, be fundamental in building aggregate models of economic behavior.

2.0 ON CONFIRMATION BIAS AND DEVIATIONS FROM BAYESIAN UPDATING

2.1 INTRODUCTION

Models of decision-making under uncertainty are central to theories of strategic and non-strategic economic interactions. In environments with imperfect information economic agents must form judgments about uncertain states of the world. These judgments, or beliefs, are then used to evaluate alternative courses of state-contingent actions. The widespread view in economic theory is that individuals update their beliefs based on information they receive via the use of Bayes' rule. Agents are assumed to posses some prior beliefs on states of the world, a set of actions that optimize their objectives, a well-defined cost of incorrect belief formation and knowledge of and skill in the use of Bayes' rule. This presumption about human behavior has been a central component of the contribution of Harsanyi (1967, 1968) who developed the theory of strategic interaction under uncertainty, and Muth (1960, 1961) who introduced to generations of macroeconomists and econometricians the role of rational beliefs in closing expectational models of non-strategic economic behavior.

The rapidly developing field of behavioral economics has identified several reasons why the above presumption on judgment under uncertainty may not provide an accurate description of the cognitive processes that underlie human decision-making. Many of these reasons rely on deviations from strict Bayesian updating such as learning and cognitive heuristics that approximate learning, as a better description of the judgment process. Of the many biases and heuristics proposed by the literature little attention has been paid by economists to notions that predict systematic biases in judgment due solely to cognition errors[1]. This chapter examines whether one such cognitive bias, confirmation bias, leads to systematic errors in judgment.

Confirmation bias is defined as an agent's tendency to seek, interpret and use evidence in a way that is biased toward confirming his already existing beliefs or hypotheses. An agent subject to confirmation bias will not hold beliefs that are identical to those held by a Bayesian observer. His belief formation given new information or the opportunity to obtain new information will be biased towards his original belief; such behavior will lead to systematic errors in judgment. This chapter provides an experimental analysis designed to investigate the extent to which subjects exhibit confirmation bias in forming probability judgments about the state of the world, under economic incentives to update beliefs in a Bayesian manner.

The next section reviews some alternatives to Bayesian updating offered by the behavioral economics literature with the aim of briefly comparing and contrasting confirmation bias with other heuristics. Section 2.3 provides an experimental design to test for confirmation bias and some alternative hypotheses in the laboratory. In the experiment subjects view signals, in the form of ping-pong balls chosen from a hidden bingo cage, drawn with replacement from one of two sets of ping-pong balls; each set contains a different mixture of black and white balls[2]. Subjects estimate the probability of each set being used based on these signals. Given this signal-extraction environment, Section 2.4 analyzes how the experiment differentiates between confirmation bias and other heuristics and biases. Section 2.5 presents the results of the experiment and Section 2.6 concludes.

The main experimental results show definite non-Bayesian behavior. Conservatism (underweighting of new evidence) is the major cause of deviations from Bayesian behavior; in addition, confirmation bias is also present. Thus, this chapter provides evidence of this particular obstacle to learning in an environment in which agents simply provide probabil-

[1] See Camerer (1995 pp. 608-609) for a review of cognitive biases that may act as "obstacles to learning".

[2] The design incorporates various treatments with respect to the ratio of black to white balls and differently colored balls whose color could be potentially confused.

ity estimates, using non-emotive stimuli, while being rewarded for truthful statements and estimates that are close to those of a hypothetical Bayesian. As such, this experimental evidence should provide incentive for continued research into the effects of cognitive biases in economic environments.

2.2 CONFIRMATION BIAS AND RELATED HEURISTICS

2.2.1 CONFIRMATION BIAS

The standard view of judgment under uncertainty and its relation to decision making under uncertainty is as follows. The economic agent is presumed to begin the decision making process with a set of prior subjective beliefs about states of the world that are updated using Bayes' rule as information arrives over time. These updated posterior beliefs are then used as probability judgments that motivate a certain action or set of actions given costs of errors and the optimization objectives.

In contrast, the psychology literature offers two suggestions towards identifying underlying cognitive processes that yield confirmation bias. First, the decision maker is more likely to seek information that can confirm a hypothesis than that which can disconfirm. Indeed, Wason's (1968) original experiment had subjects engaged in a unique card-selection task. The task consisted of subjects being provided two-sided cards that they were requested to turn over (or not) in order to confirm (or disconfirm) a pre-specified rule that the cards followed. The experiment yielded overwhelming evidence in favor of the hypothesis that subjects would more likely turn over those cards that could confirm the rule and not those cards that could disconfirm. Jones & Sugden (2001) tested for confirmation bias when subjects chose what information to purchase in order to make decisions. They found presence of the bias both when subjects purchased information and when they used it for decision making in a selection task environment. In addition, in their environment the bias persisted even when subjects repeatedly engaged in the selection task.

Second, the agent is more likely to make mistakes in perceiving signals or interpreting evidence so as to support his hypothesis. Lord, Lepper & Ross (1979) and Plous (1991) show that two subjects with opposing beliefs can interpret the same ambiguous evidence as supporting their own position. In addition Lord, Lepper & Ross (1979) demonstrate that agents may well ignore disconfirming evidence all together or give it less weight in judgment making. Rabin & Schrag's (1999) model provides a theoretical foundation to this view within a signal-extraction framework. They demonstrate theoretically that when an agent with confirmation bias perceives signals he/she is not only under-or over-confident relative to a Bayesian observer, but can also suffer from "wrongness" and may not learn despite being given an infinite amount of free information.

These analyses suggest that the cognitive processes underlying confirmation bias are as follows. First, agents seek confirmatory evidence when evaluating competing hypotheses. Second, agents place excessive weight, relative to a Bayesian, on the use of confirmatory evidence in updating their beliefs. Third, agents misperceive evidence to support beliefs even when they do not seek information. Jones & Sugden (2001) have shown that the first behavior definitely occurs under laboratory conditions when subjects are given economic incentives that reward unbiased behavior.

2.2.2 RELATED HEURISTICS

It is important to distinguish between confirmation bias and other heuristics[3]. Some heuristics and biases are related to errors in Bayesian updating. Conservatism bias describes situations in which all new information is insufficiently weighted in the updating process. The opposite bias is called overreaction and involves overweighting new information. Confirmation bias can be distinguished from these heuristics as it overweights only confirming evidence and underweights only disconfirming evidence. Next, anchoring and adjustment contains conservatism in updating posteriors, in addition to the choice of incorrect initial

[3] The seminal exposition of the psychological issues relevant to judgment under uncertainty is provided by Kahneman, Slovic & Tversky (1982).

priors. Confirmation bias does not offer an explanation for the choice of the initial prior. Next, representativeness is a heuristic that overweights samples that are representative of one particular state of the world. It is possible for any or all of these biases that cause over- or underweighting of new information to be present at the same time. If so, then the weight given to any new piece of evidence will depend on which of the heuristics is operational.

All of the above heuristics expect confirming and disconfirming evidence to be treated alike; under confirmation bias the two types of evidence are given differing weights. The experimental design in this chapter greatly diminishes the possibility of anchoring or representativeness and provides tests to distinguish between conservatism (or overreaction) and confirmation bias.

Economists have analyzed some of the heuristics described above in experiments focused on individual decision-making and in settings in which subjects interact. The main difference between the psychological and economic experiments is that in the latter subjects are motivated financially whereas in the former there is reliance on intrinsic motivation. An experimental analysis in which several judgment biases were jointly investigated in a group environment was conducted by Camerer (1987). In that analysis the heuristics of representativeness, conservatism and overreaction were observed in subjects engaged in asset trades. The economic environment was characterized by a double-oral auction and subjects were provided with priors on states of the world as well as sample information that could be used to update priors. An important environmental characteristic of the biases investigated in Camerer (1987) is that subjects observed each other's behavior. In an individual decision making environment, Grether (1980) found that subjects making probability estimates exhibited representativeness. El-Gamal & Grether (1995) formulated a statistical procedure in which the rules of thumb actually used by subjects could be identified. They found that subjects used Bayes' rule, representativeness and conservatism in that order of importance. These studies have primarily elicited responses of the following variety: "Do you think that the [state of the world] is A or B?". The present analysis is innovative in that it elicits and analyses probability judgments of the following variety[4]: "What do you think is the probability of [the state of the world A]?".

In summary, confirmation bias is investigated in an environment where agents infer states of the world through possibly 'ambiguous' evidence via the use of informative signals. The approach is to test confirmation bias as an individual phenomenon as this bias needs to be first investigated in an environment in which subjects have a non-strategic incentive to update in a Bayesian manner. Having characterized the bias in such an environment future analyses can investigate the effects of this bias in strategic environments with increased clarity.

With respect to the experimental design, the first focus is on the case in which agents do not seek information but are provided instead with costless and clear signals. However, confirmation bias may also exist in environments without information seeking if it is based on misperception of signals, thus the second focus of the design is on the case in which there are ambiguous signals. Given this dual focus ambiguity is modeled both as differing signal correlations as well as through stimuli that by construction can be misperceived. These latter stimuli are can be of two types, emotive and non-emotive, since confirmation bias may be more likely with emotive stimuli given the analysis of Lord, Lepper & Ross (1979). Positive empirical results with non-emotive stimuli will substantially increase the applicability of the bias in theoretical and applied analyses of dynamic decision making under uncertainty[5].

2.3 EXPERIMENTAL DESIGN

The experimental design in this chapter is inspired by Grether's (1980) balls in the urns experiments[6]. In the first treatment, two sets of black and white ping-pong balls were

[4]Indeed Dominitz & Hung (2003) also elicit probability judgements within the context of informational cascades in the laboratory.

[5]Attempts were made to implement an emotive treatment that would be equivalent, in terms of the experimental theatre involved, to the treatments with non-emotive stimuli. However, pilot tests indicated that subjects did not view the draws in the emotive treatment as being random relative to the non-emotive treatment. Planned future work will incorporate this feature.

[6]See Appendix A for the instructions given to subjects.

employed. The “more black” set had seven black balls and three white balls and the “more white” set had three black balls and three white balls. The second treatment had six black balls and four white balls in the “more black” set and four black balls and six white balls in the “more white” set. The third treatment had seven dark gray balls and three light gray balls in the “more dark” set and three dark gray balls and seven light gray balls in the “more light” set. These treatments are referred to as the 70/30 Black/White treatment (or Treatment A), the 60/40 Black/White treatment (or Treatment B), and the 70/30 Dark/Light treatment (or Treatment C) respectively.

For each round, one set was selected at random and placed in a covered bingo cage. Subjects then recorded their probability estimates for the chance that the set in the bingo cage was “more black” and the chance that it was “more white”. Ten balls were drawn with replacement from the bingo cage. For the Black/White treatments (but not the Dark/Light treatments) the experimenter announced the color of the ball. After each draw, the subjects recorded the color of the ball and their new probability estimates on their record sheets. After all ten draws, the bingo cage was uncovered to reveal which set of balls had been used.

Each session began with a practice round where the procedure was demonstrated in the front of the room. The six rounds of the actual experiment were shown on videotape so that multiple experimental sessions could be conducted using the same sequence of draws.

A pilot, with payment in candy, run on one of the author’s classes induced some limits on the sequences of draws that were videotaped. First, the subjects lost interest after six or seven rounds, so six rounds were used for the experiment. Second, some randomly generated sequences contained few or no cases of confirming and disconfirming evidence, so sequences were limited to those that had at least two cases each of confirming and disconfirming evidence. Six randomly generated sequences were used, which met this criterion from the 70/30 Black/White treatment. It was imperative that the subjects to see the same signals for each treatment. So many procedures were taped until the same or symmetric (black and white reversed) sequences for the other two treatments were obtained.

After all six rounds, one draw from one round was randomly selected for the payoff calculation. The payoff mechanism was designed to induce risk neutrality and truth telling about the probability estimates. Subjects played one of two gambles in order to receive monetary payoffs. Gamble 1 (G_1) was based on the subject's reported probability estimate for the payoff round and draw. If the set in the bingo cage was the one they estimated as more likely, the subject received a \$15 payment in addition to the \$5 show up fee. Gamble 2 (G_1) was based on a set of two randomly generated numbers. The "lucky number" was selected by drawing from a set of ping-pong balls numbered from 51 to 100. Then two ten sided dice were rolled to generate another number from 1 to 100. If the dice roll was less than or equal to the "lucky number", the subject received the \$15 payment. The subject's expected probability of winning the first gamble was his or her estimated probability of the more likely set. The subject's expected probability of winning the second gamble is the "lucky number" divided by one hundred. The subject played whichever gamble had the higher reported probability of winning for him or her, so the mechanism induced truth telling regardless of the subject's risk preference[7].

2.4 ANALYTICAL FRAMEWORK

2.4.1 FRAMEWORK SUMMARY

A perfectly Bayesian subject would calculate the probability of the "more black" set being in the bingo cage after draw t, as,

$$P_t(more\ black \mid b_t, w_t) = \frac{\theta^{(b_t - w_t)}}{\theta^{(b_t - w_t)} + (1-\theta)^{(b_t - w_t)}} \tag{2.1}$$

where the proportion of black in the "more black" set is θ and in the "more white set is $1-\theta$, and b black balls and w white balls have been drawn[8]. It is important to note that the Bayesian does not care about the order of the draws of the balls. Each time the Bayesian sees

[7] Figure 30 in Appendix C illustrates the payoff procedure.
[8] See Edwards (1982) for an example of psychology experiments in this genre.

another draw, the quantity $(b_t - w_t)$ will increase by exactly one. In this perfectly Bayesian environment the log of the odds ratio is given by,

$$\pi_t = \ln\left(\frac{P_t(\textit{more black} \mid b_t, w_t)}{P_t(\textit{more white} \mid b_t, w_t)}\right) = (b_t - w_t)\ln\left(\frac{\theta}{1-\theta}\right) \tag{2.2}$$

and it is seen that for the Bayesian, the log odds ratio is linear in balls drawn. In the 70/30 treatments, $\pi_t = (b_t - w_t) \times 0.847$, and after each new draw, the log odds ratio will be updated by ± 0.847. In the 60/40 treatment the update amount is 0.405. Clearly if subjects deviate from Bayesian behavior due to employment of the conservatism heuristic, one would expect to see consistently smaller updates. If subjects overreact, the update of the log odds will be greater than 0.847 (or 0.405).

Bayesians will always estimate the probability before the first draw as $50\% - 50\%$ or even odds. If subjects are using the anchoring and adjustment heuristic, they will not necessarily start at even odds. In the pilot data it was found that many students held a belief in the gambler's fallacy: if the set in the previous round was "more black", the current round was more likely to use "more white". Or they believed in the hot hands fallacy - that gambling follows a run of luck - if the set in the previous round was "more black", this round was also more likely to use "more black". Regardless of their initial belief, subjects using the anchoring and adjustment heuristic will update their probability estimate in the proper direction after each draw.

In order to reduce the possibility of subjects using the representativeness bias the experiment employed ten balls in each set and ten draws. Only the last draw could possibly be representative of either set.

A subject exhibits confirmation bias in this experiment is he/she perceives or uses new information differently depending on whether it confirms or disconfirms his/her previously held belief. One can tell whether the information is confirming based on the prior odds reported by the subject. If $\pi_{it-1} > 0$, then the subject believes the bingo cage is more likely to contain the "more black" set than the "more white" set. In this case, a black ball would be confirming information and a white ball would be disconfirming information. If the prior log odds indicate that the subject believes both sets to be equally likely ($\pi_{it-1} = 0$), then this was referred to as the neutral case, regardless of what color ball is drawn. Note that the same information can yield different information conditions for different subjects, if their prior beliefs differ. A black ball will be confirming to a subject whose prior odds were 70% "more black", neutral to a subject whose prior odds were 50% "more black", and disconfirming to a subject whose prior odds were 45% "more black".

A subject may very likely exhibit more than one bias. The key to identifying confirmation bias is to find differences in the subject's behavior for the different information conditions. Rabin & Schrag (1999) put forth an explanation for confirmation bias as arising from the misperception of the signal. One can test for this effect by contrasting the Black/White treatment, where the signal cannot be misperceived with the Dark/Light treatment where misperception is possible. Their model also implies that the weaker the correlation between the signal and the state of the world, the more likely confirmation bias is to lead agents astray. To test for this effect two treatments using more (70/30) and less (60/40) correlated signals were employed. The remainder of this section outlines in detail the data manipulations for the reported results.

2.4.2 MODEL SPECIFICATION AND INTERPRETATION

The experimental design provides data on subjects' probability reports. Denoting subjects by i, draws within a round by t and the more black set as A the following log-odds ratio is constructed,

$$\widetilde{\pi}_{it} = \log\left(\frac{P(A \mid S^t)_{it}}{1 - P(A \mid S^t)_{it}}\right) \tag{2.3}$$

where $S^t = \{s_t, ..., s_0\}$ denotes the history of signals ($B(lack)$ or $W(hite)$) at each draw. The data are truncated to lie in the [0.05, 0.95] interval so that the above ratio is meaningful[9]. Next a variable is constructed that measures whether subjects think a B or W signal is more

[9] Some subjects did report probabilities of 0 and 1, however, alternate truncation assumptions did not change the results significantly.

likely for the next draw, as follows,

$$E_{it} = \left\{ \begin{array}{ll} B & if\ P(A \mid S^{t-1})_{it-1} > 0.5 \\ W & if\ P(A \mid S^{t-1})_{it-1} < 0.5 \\ N & if\ P(A \mid S^{t-1})_{it-1} = 0.5 \end{array} \right\} \tag{2.4}$$

This variable is then used to construct log odds from the raw data that show the probability of the more expected state regardless of the color of the bingo ball, that is,

$$\pi_{it} = \left\{ \begin{array}{ll} -\widetilde{\pi}_{it} & if\ E_{it} = W \\ \widetilde{\pi}_{it} & if\ E_{it} = B\ or\ E_{it} = N \end{array} \right\} \tag{2.5}$$

The Bayesian updater in this environment does not differentiate between confirming and disconfirming information, however, subjects may, prompting the construction of the following dummy variables.

$$C_{it} = \left\{ \begin{array}{ll} 1 & if\ (E_{it} = W\ and\ s_t = B)\ or\ (E_{it} = W\ and\ s_t = W) \\ 0 & otherwise \end{array} \right\} \tag{2.6}$$

$$D_{it} = \left\{ \begin{array}{ll} 1 & if\ (E_{it} = B\ and\ s_t = W)\ or\ (E_{it} = W\ and\ s_t = B) \\ 0 & otherwise \end{array} \right\} \tag{2.7}$$

That is, the above variables measure whether a signal received is viewed as confirmed or disconfirmed from the point of view of a subject.

Next, confirmation bias may occur in more difficult cognitive decision making tasks. In the experimental design, when subjects have seen equal numbers of black and white balls, the Bayesian probability of 0.5 is very easy to calculate and equal numbers of black and white signals occur only in disconfirming evidence cases[10]. Therefore, the D_{it} dummy is differentiated to separate the "easy" disconfirming cases from other cases, as follows.

$$P^*_{it} = 1 \quad if\ P(A \mid S^t) = 0.5, \quad 0\ otherwise \tag{2.8}$$

$$D^*_{it} = D_{it} \times P^*_{it} \tag{2.9}$$

[10] It is of relevance to note that, given the definitions of confirming and disconfirming pieces of evidence, a piece of confirming evidence sends a probability report away from the prior, while a piece of disconfirming evidence may send a probability report towards the prior. This holds for hypothetical Bayesians and subjects.

Given the above variable definitions the following regression model is estimated and tested for various types of updating behavior, as follows. Consider the following model for each treatment,

$$\pi_{it} = \alpha_0 + \alpha_1 \pi_{it-1} + \alpha_2 C_{it} + \alpha_3 D_{it} + \alpha_4 D^*_{it} + \alpha_5 [C_{it} \times \pi_{it-1}] + \xi_{1it} \tag{2.10}$$

where ξ_{1it} is the idiosyncratic regression error and the data have been stacked across rounds[11]. The hypothesis tests conducted on this model derive from the three possible updating behaviors that the design allows for: Bayesian updating, conservatism and confirmation bias or a combination of the latter two heuristics. The null of Bayesian behavior is given by,

$$H_0^1 : \alpha_0 + \alpha_2 = \log \frac{\theta}{1-\theta} \cap \alpha_0 + \alpha_3 + \alpha_4 = -\log \frac{\theta}{1-\theta} \cap \alpha_1 = 1 \cap \alpha_5 = 0 \tag{2.11}$$

Further, the null of no confirmation bias is given by,

$$H_0^2 : 2\alpha_1 + \alpha_5 = 2 \cap \alpha_0 + \alpha_2 = -(\alpha_0 + \alpha_3) \tag{2.12}$$

Equivalently, the above hypothesis can be re-stated in inequalities and confirmation bias would require that it be accepted.

The model and the related hypothesis tests presented so far can be explained graphically which can assist in interpretation of the experimental data. The dummy variables C_{it} and D_{it} can be constructed for both a hypothetical Bayesian and a subject. For a Bayesian, the difference between the two sorts of information should be statistically insignificant in explaining the log-odds ratios. Indeed, in (π_{it}, π_{it-1}) space, the regression lines are presented in Figure 31 of Appendix C. The behavior of a Bayesian updater is represented by an intercept of $\log\left(\frac{\theta}{1-\theta}\right)$ or $-\log\left(\frac{\theta}{1-\theta}\right)$ and a slope of one. In Figure 31, under conservatism, the regression lines would lie beneath those of the hypothetical Bayesian but would be parallel. Under confirmation bias the regression lines would not be parallel to those of a Bayesian nor would they be parallel to one another if confirming evidence is treated differently from disconfirming evidence. the hypothesis test presented above reflect these notions about the degree to which estimated regression lines are parallel or not relative to those of a hypothetical Bayesian.

[11] Round-by-round regressions yielded qualitatively the same results, however, since there were relatively few cases of $C_{it} = 1$ the significance of confirming evidence is clearer in the stacked regression.

2.4.3 PATH DEPENDENCE AND CONFIRMATION BIAS

The above simple model assumes that all of the information history is contained in the reported probability estimate. That is, subjects engage in only one-step updating such that each probability report contains all the historically relevant information. However, subjects may arrive at the same probability estimate with different information histories. That is, there may be path-dependence in updating. A simple measure of path dependence for information in this environment is to count how many pieces of confirming evidence a subject has seen in a row, or, how many pieces of disconfirming evidence a subject has seen in a row. Therefore consider the following variables constructed from the above definitions of C_{it} and D_{it}.

$$C_{1it} = \left\{ \begin{array}{ll} 1 & if\ C_{it} = 1\ and\ C_{it-1} = 0 \\ 0 & otherwise \end{array} \right\} \tag{2.13}$$

$$C_{2it} = \left\{ \begin{array}{ll} 1 & if\ C_{it} = 1\ and\ C_{it-1} = 1\ and\ C_{it-2} = 0 \\ 0 & otherwise \end{array} \right\} \tag{2.14}$$

$$C_{3it} = \left\{ \begin{array}{ll} 1 & if\ C_{it} = 1\ and\ C_{it-1} = 1\ and\ C_{it-2} = 1\ and\ C_{it-3} = 0 \\ 0 & otherwise \end{array} \right\} \tag{2.15}$$

$$C_{Hit} = \left\{ \begin{array}{ll} 1 & if\ C_{it} = 1\ and\ C_{1it} = 0\ and\ C_{2it} = 0\ and\ C_{3it} = 0 \\ 0 & otherwise \end{array} \right\} \tag{2.16}$$

The above definitions decompose the confirming cases (C_{it}) into whether a subject has seen one, two, three or more such cases in a given round[12]. The definitions below provide the same sequence for disconfirming cases. Together, the two sets of variables account for a number of different paths that a subject can take in reporting probabilities with differentiation based

[12] The choice of three cases is a result of an analysis of the data that indicated very few higher level cases.

on confirming versus disconfirming evidence.

$$D_{1it} = \left\{ \begin{array}{ll} 1 & if\ D_{it} = 1\ and\ D_{it-1} = 0 \\ 0 & otherwise \end{array} \right\} \tag{2.17}$$

$$D_{2it} = \left\{ \begin{array}{ll} 1 & if\ D_{it} = 1\ and\ D_{it-1} = 1\ and\ D_{it-2} = 0 \\ 0 & otherwise \end{array} \right\} \tag{2.18}$$

$$D_{3it} = \left\{ \begin{array}{ll} 1 & if\ D_{it} = 1\ and\ D_{it-1} = 1\ and\ D_{it-2} = 1\ and\ D_{it-3} = 0 \\ 0 & otherwise \end{array} \right\} \tag{2.19}$$

$$D_{Hit} = \left\{ \begin{array}{ll} 1 & if\ D_{it} = 1\ and\ D_{1it} = 0\ and\ D_{2it} = 0\ and\ D_{3it} = 0 \\ 0 & otherwise \end{array} \right\} \tag{2.20}$$

Next, in the pilot of the experimental procedure subjects reported a strong distaste for any draw that resulted in an information path of equal numbers of black and white balls, indicating that the odds were back to 0.5-0.5, as noted for the simpler model above. Therefore, in those cases of disconfirming evidence which result in a history of equal numbers of A and B draws the following variables can be constructed.

$$D^*_{kit} = D_{kit} \times P^*_{it} \quad k = 1, 2, 3, H \tag{2.21}$$

Given these additional variable definitions, the regression model is now given by,

$$\pi_{it} = \left\{ \begin{array}{c} \beta_0 + \beta_1 \pi_{it-1} + \beta_{21} C_{1it} + \beta_{22} C_{2it} + \beta_{23} C_{3it} + \beta_{31} D_{1it} + \beta_{32} D_{2it} + \beta_{33} D_{3it} \\ +\beta_{41} D^*_{1it} + \beta_{42} D^*_{2it} + \beta_{43} D^*_{3it} + \beta_5 [C_{it} \times \pi_{it-1}] + \xi_{2it} \end{array} \right\} \tag{2.22}$$

with the associated hypothesis test of no confirmation bias,

$$H^3_0 : \left\{ \begin{array}{c} 2\beta_1 + \beta_5 = 2 \cap \beta_0 + \beta_{21} = -(\beta_0 + \beta_{31}) \cap \\ \beta_0 + \beta_{22} = -(\beta_0 + \beta_{32}) \cap \beta_0 + \beta_{23} = -(\beta_0 + \beta_{33}) \end{array} \right\} \tag{2.23}$$

so that rejection of H^3_0 would imply the presence of confirmation bias even with varying paths of information.

2.4.4 DESCRIPTIVE TESTS

The above framework provides a regression approach for testing various updating behaviors. In addition to the above approach, tests on the means of the following variables can also be conducted in order to provide inference on conservatism/overreaction and confirmation bias. Consider variations of the log-odds updates defined as,

$$\upsilon_{it} = \left\{ \begin{array}{ll} \pi_{it} - \pi_{it-1} - \log \frac{\theta}{1-\theta} & if\ C_{it} = 1 \\ \pi_{it-1} - \pi_{it} - \log \frac{\theta}{1-\theta} & if\ D_{it} = 1 \\ \pi_{it} - \log \frac{\theta}{1-\theta} & if\ C_{it} = 0 \cap D_{it} = 0 \end{array} \right\} \tag{2.24}$$

The variable therefore measures the step update for each subject in each round for each treatment under confirming, disconfirming and neutral cases. Thus, in order to test for conservatism the following hypothesis can be conducted,

$$H_0^4 : mean(\upsilon_{it}) = \log \frac{\theta}{1-\theta} \tag{2.25}$$

Next, tests can be conducted to discern whether mean updates are different under confirming, disconfirming and neutral cases,

$$H_0^5 : mean(\upsilon_{it} \mid C_{it} = 1) = mean(\upsilon_{it} \mid D_{it} = 1) \tag{2.26}$$

$$H_0^6 : mean(\upsilon_{it} \mid C_{it} = 1) = mean(\upsilon_{it} \mid C_{it} = 0 \cap D_{it} = 0) \tag{2.27}$$

$$H_0^7 : mean(\upsilon_{it} \mid D_{it} = 1) = mean(\upsilon_{it} \mid C_{it} = 0 \cap D_{it} = 0) \tag{2.28}$$

These tests can be conducted on stacked data or for each subject in a treatment. In addition, tests can be conducted in order to discern whether the mean of confirming updates differs from disconfirming or neutral cases. These tests may also be conducted on stacked data or for each subject and the next section presents a selection of such results.

In summary, in order to analyze the data resulting from the experiments the above framework employs various steps. The first step is to convert the data into log-odds updates which are constant given the theoretical likelihood of the design. Next, variables are constructed that reflect whether, given a reported probability estimate, a subject has seen evidence in the form of signal that can be deemed as confirming or disconfirming a previously held belief. These variables are then further decomposed depending on various paths of information that could lead to a reported probability, that is, how many times has the subject seen confirming or disconfirming evidence? Finally, the updates themselves are analyzed in a non-regression framework. Thus, the framework provides a series of tests that can be constructed on stacked round-by-round or individual data; the next section provides these results.

2.5 RESULTS

This section reports the results of the empirical analyses conducted on the data using the analytical framework described above. The results are oriented around the three hypotheses of relevance: Bayesian behavior, conservatism and confirmation bias.

- **Are Subjects' Bayesian?**

As a description of the raw data, Figures 32-49 in Appendix C presents the average reported probabilities (with one standard deviation bands) along with those of a hypothetical Bayesian[13]. The plots clearly indicate that even though the hypothetical Bayesian often lies within a one standard deviation band of the average, at any given draw in any given round the average probability report is less than that of a Bayesian.

Next, Table 8 in Appendix B presents the estimation results of equation (2.10), the simple model[14]. The model is estimated with fixed effects which are prevalent in all three treatments. The coefficients are of the correct sign in all of the treatments although the confirming slope coefficient, α_5, estimates to be near zero in Treatment C. Table 8 also presents the results of the Bayesian hypothesis test (H_0^1) and the test of no confirmation bias (H_0^2). The data reject both hypotheses in all three treatments[15]. Indeed Figures 50-52

[13]The great majority of subjects reported uniform priors at the start of each round with very few expections. Therefore the design was able to induce correct priors before the updating portion of the experiment in each treatment.

[14]Note that in Tables 8-9 H_0^F refers to the null of no fixed effects and hypothesis tests are presented as $(F, Prob > F)$.

[15]Panel unit root tests indicated the rejection of a unit root in all treatments.

in Appendix C present the estimated regression lines versus their Bayesian counterparts for all three treatments. The fact that the data suggest non-Bayesian behavior in clearly seen here.

- **Are Subjects' Conservative?**

As in the case of the Bayesian hypothesis, Figures 50-52 in Appendix C provide a casual verification of conservative behavior. Further, the Wilcoxon tests reported in Table 10 suggest that the null of no conservatism as represented by H_0^4 is rejected across treatments. Overall, the data prefer non-Bayesian conservative behavior as witnessed by the estimated regression lines which to a large extent lie within the bounds of Bayesian. Indeed, Figures 50-52 suggest that subjects are both conservative and possibly exhibit confirmation bias, the hypothesis investigated next.

- **Do Subjects' Exhibit Confirmation Bias?**

Table 8 in Appendix B presents the estimation results for the simple model, Table 9 presents the results for the model with decomposed confirming and disconfirming cases. The nulls of no confirmation bias (H_0^2 and H_0^3) are rejected in both models across treatments. Further, Table 9 continues to accept the fixed effects assumption and the estimates are of the correct sign across treatments. The regression lines in Figures 50-52 also suggest that subjects treat confirming and disconfirming information differently. Indeed it is of importance to note that the estimated regression lines are very similar in Treatments A and C relative to those of Treatment B. This suggests that physical misperception of signals may be as important as clear stimuli in generating confirmation bias. Indeed, it seems that the more difficult proportion of $\theta = 0.6$ of Treatment B leads to increased differentiation between confirming and disconfirming evidence.

Next, Table 10 presents the test results for hypotheses $H_0^5 - H_0^7$. In particular, across treatments, the Mann-Whitney tests suggest that confirming updates are different from neutral cases, as are the disconfirming updates. However, confirming updates are different from non-confirming ones only in Treatment A. Table 11 in Appendix B reports the proportion of subjects for whom the mean update under confirming evidence is different from that under disconfirming evidence at the 10% significance level, that is, the test results of $H_0^5 - H_0^7$ for each subject. The results presented in Table 11 suggest that for roughly 20% of the subject the mean of the updates under confirming evidence is different than that under disconfirming evidence. Overall, the results suggest non-Bayesian behavior with strong evidence in favor of conservatism with the presence of confirmation bias.

The main result, that subjects view confirming and disconfirming information differently, can be viewed via a simple plot of the reported probabilities. Figures 53-55 in Appendix C provide bubble plots of the reported estimates relative to the values that would be computed by a hypothetical Bayesian for each treatment. The figures have been scaled so that the bubbles can be clearly viewed as in some cases there is overlap. The size of the bubbles reflects the number of subjects who were found to fall in the confirming, disconfirming and neutral categories, a larger bubble represents a larger number of subjects. The plots clearly indicate that around the 50% mark most subjects were neutral in their beliefs, however, as the rounds progressed within a treatment, confirming cases began to emerge.

Finally, it is important to note that while confirmation bias exists in the experimental environment considered here, it is not as strong a bias as when agents are involved in updating with emotive stimuli. However, what may be of relevance here is that the bias does exist, albeit to a smaller extent, in an environment which is often considered as a benchmark in economic theory.

2.6 CONCLUSION

In analyzing deviations from Bayesian updating, an important question is whether economic agents exhibit cognitive biases. In this chapter one such bias, confirmation bias, is investigated in a laboratory setting within the context of individuals reporting probability estimates. These probability estimates are solicited having induced risk-neutral behavior with truthful revelation through a payoff mechanism that rewards probability reports that are close to those of a hypothetical Bayesian.

The experimental data displays non-Bayesian behavior and provides evidence of the conservatism heuristic with the presence of confirmation bias. The literature has documented the presence of this bias with emotive stimuli instead of the non-emotive stimuli employed here. The literature has also documented the bias within the context of a decision-making task. However, the literature has not documented the presence of the bias when stimuli are non-emotive and subjects must only report probability estimates as opposed to engaging in a full decision task. This chapter provides an experimental environment, analytical method and empirical evidence suggesting the presence of confirmation bias even when stimuli are non-emotive and agents report probability estimates. Future research may evaluate the presence of this bias in strategic market settings in order to bolster the evidence provided in this chapter.

3.0 IS HIGH CAPACITY UTILIZATION NO LONGER INFLATIONARY

3.1 INTRODUCTION

Industrial capacity utilization measures are viewed by monetary authorities as useful inflationary indicators. As a resource utilization measure, capacity utilization is defined as the ratio of actual to capacity output, where the latter quantity is typically estimated with one of several available filtering techniques. In Canada the aggregate capacity utilization series is benchmarked to survey data, providing a unique opportunity to examine aggregate data that reflect actual business conditions[1]. However, recently for Canada, capacity utilization levels have been high without inducing increases in inflation. Figure 56 in Appendix C provides a plot of capacity utilization and core inflation. The plot suggests that through time the relationship between capacity utilization and inflation may have diminished in terms of levels and/or co-movements. Further, in recent years, the series has breached the well accepted level of the non-accelerating inflationary rate of capacity utilization (NAICU) of 82% without corresponding increases in inflation.

These observations prompt two natural questions: is high capacity utilization no longer inflationary, and if not, why? This chapter addresses these questions by first establishing

[1] See *Fixed Capital Flows and Stocks (Statistics Canada)* for details on the construction of aggregate capacity utilization series using survey responses. The relevant survey is the Capital Expenditures Survey that requests firms to answer the following question. "For the year [*t*], this plant operated at what percentage of its capacity?", [where], "Capacity is defined as maximum production attainable under normal conditions. With regard to normal conditions, please follow the company's operating practices with respect to the use of productive facilities, overtime, workshifts, holidays, etc. When any of your facilities permit the substitution of one product for another, use a product mix at capacity which is most similar to the composition of your [year *t*] output."

relevant stylized facts drawn from empirical models of capacity utilization-inflation Phillips curves. The estimation results indicate that the effect of capacity utilization on inflation has diminished over time, and that there are statistically significant breaks in the relationship. These breaks correspond to economic events that can be interpreted as having increased the degree of competitiveness and, to a lesser extent, decreased the level of nominal rigidities in the Canadian economy. In order to qualitatively lend credence to this conjecture, this chapter estimates the dynamic stochastic general equilibrium model of Ireland (2003). The model incorporates monopolistically competitive firms who face time-varying cost-push shocks and Rotemberg (1982) style nominal menu costs of adjusting prices. As a result the model delivers a capacity utilization-inflation trade-off that is in part a function of the degree of competitiveness and nominal rigidities present in the economy. The empirical exercise demonstrates that the estimated aggregate price mark-up may have decreased, as may have the degree of nominal rigidity in the Canadian economy, lending credence to the conjectures behind the observed breaks in the capacity utilization-inflation relationship. The main conclusion is that the economy may be tending towards characterizations provided by competitive equilibrium flexible price models which do not necessarily predict a structural relation between inflation and real resource utilization measures.

The remainder of the chapter is structured as follows. In Section 3.2, empirical models of the capacity utilization-inflation Phillips curve are specified under the assumption that inflation expectations are backward looking and under the assumption that these expectations may also be forward looking, given that the Bank of Canada instituted an inflation targeting regime in the early 1990's. The specifications take the form of time-varying parameter models (as per Kim & Nelson (1999)), single structural break models (as per Hansen (2000)) and multiple structural break models (as per Bai & Perron (1998)). Further, the timing of the breaks are estimated using the likelihood based procedures as per DeJong et al (2004). Estimation results, presented in Section 3.3, indicate that there is a steady deterioration in the capacity utilization-inflation relationship through time.

The central conjecture in this chapter on the reasons driving the stylized facts, is that the Canadian economy has become more competitive and, to a lesser extent, faces reduced nominal rigidities. An explanation of a leading positive relationship between capacity utilization and inflation is as follows. If firms are monopolistic competitors then when faced with, say, a positive demand shock, they will ratchet up production relative to a fixed capacity. Increased production will drive up costs, which will be passed on to consumers through the price-setting power of firms resulting in an increase in inflation. This increase in inflation would be associated with high capacity utilization as a result of the increase in production relative to capacity. However, if firms are competitive then they will be unable to pass on cost increases, reducing the effect on inflation[2]. In Section 3.4 of this chapter a micro-founded New Keynesian model by Ireland (2003) is described that captures this intuition. In Section 3.5, the model is estimated to demonstrate that the aggregate price mark-up has decreased, and that the degree to which nominal rigidities are present may have decreased. As a result, the statistical findings of Section 3.3 are explored formally and the chapter concludes in Section 3.6 with a summary of the stylized facts drawn and the explanations given for them.

The conclusions put forth in this chapter do not contradict related recent findings. Indeed, Paquet & Robidoux (2001) find that, in decomposing the Solow residual, an assumption that the Canadian economy is described by perfect competition and constant returns to scale best fits the data. In addition, Paquet & Robidoux (2001) find that when capital stocks are adjusted for capital utilization rates in Canada, productivity shocks are exogenous to real and monetary forces. The analysis in this chapter is complementary to these findings. Thus the main contribution of this chapter is to first develop stylized facts for a variable that clearly reflects business conditions due to its' measurement methodology and then attempt to explain the facts in a simple well-known framework.

Finally, the analysis in this chapter also acts as an application of an emerging synthesis between New Keynesian and 'real' business cycle models. Indeed Clarida et al. (2000) and Ireland (2002, 2003) among others attempt to marry the advantages afforded by real

[2]See Shapiro (1989) for details on the two transmission mechanisms and an early introduction to the issue of capacity utilization-inflation dynamics for the United States. Finn (1996) demonstrates that a competitive equilibrium model with a role for energy shocks adequately explains the capacity utilization-inflation relationship for the United States.

business cycle transmissions of technology and preference shocks with non-Walrasian shocks, such as the cost-push shocks considered here in analyzing the capacity utilization-inflation relationship. This synthesis is emerging as fertile ground, with strong micro-foundations[3], to sort out the competing sources of business cycle fluctuations. This chapter adds to the synthesis by analyzing a relationship between inflation and a macroeconomic variable that results from a comprehensive survey of firms.

3.2 EMPIRICAL MODELS

In order to determine whether there has been a break over time in the statistical relationship between capacity utilization and inflation, continuous and discrete break tests must be robust across assumptions on inflation expectations. Within the time period considered in this section, 1975QI-2002QIV, the Bank of Canada implemented two main changes in monetary policy. First, in the 1980's the Bank of Canada decelerated in order to reduce the high and variable inflation Canada had experienced in previous decades. Second, the Bank of Canada instituted an inflation targeting regime in 1991QI and since then has moved towards a regime of almost complete transparency of monetary policy. Therefore two types of models are specified: a backward looking model and a mixture model that combines backward looking and forward looking inflation expectations.

3.2.1 BACKWARD LOOKING EXPECTATIONS

Consider the standard predictive capacity utilization-inflation Phillips Curve[4],

$$\pi_t = \alpha_0 + \alpha_1 u_{t-1} + \pi_t^e \tag{3.1}$$

[3] Here micro-foundations refer to the fact that New Keynesian models now specify IS and Phillips curves based on explicit optimization given assumptions, versus ad-hoc specifications of these relations.

[4] See Emery & Chang (1997) and references therein for a background on utilization-inflation Phillips curves that have been estimated in the literature.

where π_t represents inflation, u_t represents capacity utilization and π_t^e represents expected inflation. The backward looking expectations assumption specifies inflation expectations as a lag over past inflation, with the lag coefficients summing to unity. A lag specification often employed for Canada (see Johnson (2002), Longworth (2002) and references therein) yields,

$$\pi_t = \alpha_0 + \alpha_1 u_{t-1} + \alpha_2 \pi_{t-1} + \alpha_3 \pi_{t-2}, \quad \alpha_2 + \alpha_3 = 1 \tag{3.2}$$

The unconstrained equation (3.2) yields the following backward looking expectations empirical specification,

$$\pi_t = \alpha_0 + \alpha_1 u_{t-1} + \alpha_2 \pi_{t-1} + \alpha_3 \pi_{t-2} + \alpha_4 x_{t-1} + \varepsilon_{1t} \tag{3.3}$$

where x_{t-1} is the change in the Canada-U.S. real exchange rate that is included to account for the small and open nature of the Canadian economy.

3.2.2 MIXTURE EXPECTATIONS

Under the assumption of mixture expectations there is weight on forward looking expectations, thus the analog of (3.2) is given by,

$$\pi_t = \alpha_0 + \alpha_1 u_{t-1} + \alpha_2 \pi_{t-1} + \alpha_3 \pi_{t-2} + \alpha_5 \pi_t^e, \quad \alpha_5 = 1 - \alpha_2 - \alpha_3 \tag{3.4}$$

where π_t^e represents period t's expectation of inflation for period $t+1$ and is a measured variable[5]. The unconstrained version of (3.4) yields the following mixture expectations empirical specification,

$$\pi_t = \alpha_0 + \alpha_1 u_{t-1} + \alpha_2 \pi_{t-1} + \alpha_3 \pi_{t-2} + \alpha_4 x_{t-1} + \alpha_5 \pi_t^e + \varepsilon_{2t} \tag{3.5}$$

[5] Data were obtained from the Conference Board of Canada's survey of forecasters to proxy for inflation expectations. As this time series begins in 1975QI, the analysis was conducted for the sample period 1975QI-2002QIV. Alternate series for inflation expectations, constructed from actual inflation rates, does allow for a longer time dimension, however, yields the same qualitative results. The main advantage of the survey series is that it allows the model to incorporate actual expectations. The remaining data on core inflation (i.e. inflation less the influence of indirect taxes, energy and other volatile components), capacity utilization and exhange rates were obtained from the Department of Finance Canada. The data collected were as close an approximation to a real-time dataset as possible.

which can be interpreted as nesting the backward looking model. Indeed the models are specified without restricting them to their respective inflation expectations assumptions. The models are estimated in this unrestricted form as it is assumed that no one assumption on expectations can reflect reality. Further, by estimating unrestricted versions it can be seen to what extent forward looking expectations matter by verifying whether the estimate of α_5 is significant and positive.

In order to determine whether the relationship has deteriorated under backward looking or mixture expectations, the above two models are estimated with discrete break techniques as well as a time-varying parameter approach; the latter would account for a continuously deteriorating relationship. There are several techniques that can be employed in evaluating whether a regression suffers from breaks in its' parameters across time. The focus in the present analysis is on endogenously estimating any breaks (as opposed to, say, inferring breaks using rolling Chow tests), and evaluating whether the relationships in (3.3) and (3.5) are deteriorating over time. Therefore, the next section details the estimation methods employed.

3.2.3 ESTIMATION METHODS

The time-varying parameter models are estimated using the Kalman Filter as discussed in Kim & Nelson (1999). In particular, given the following general regression model,

$$y_t = x_t\beta + \varepsilon_t \tag{3.6}$$

where x is a matrix of regressors (possibly containing lagged values of y) and β is a vector of coefficients, Kim & Nelson (1999) discuss a time-varying parameter version of (3.6) given by,

$$\begin{aligned} y_t &= x_t\beta_t + e_t \\ \beta_t &= \beta_{t-1} + \upsilon_t \\ e_t &\sim NID(0, \sigma_e^2), \quad \upsilon_t \sim NID(0, Q) \end{aligned} \tag{3.7}$$

The inferential focus is on the estimates of the standard deviation of each of the time-varying parameters (where Q is the diagonal variance-covariance matrix), the resulting time varying estimates $(\widehat{\beta}_t)$, and the model's conditional variances and forecast errors which identify periods of volatility. The backward looking and mixture models presented above are estimated using this general framework.

Time-varying parameter estimation evaluates any continuous breaks, inference can be strengthened with discrete breaks tests. If there are any shifts then structural break models can be used to date them. For this purpose, the methods of Hansen (2000) and Bai & Perron (1998) are employed to identify structural breaks. The inferential focus in Hansen (2000) is on identifying one possible break over time in a model such as that in (3.6), whereas the inferential focus in Bai & Perron (1998) is on the following four types of break tests. The first is a test of zero versus a specific number of breaks (say, k), denoted the $\sup F(0|k)$ tests. The second type, denoted the $D\max$ tests are tests of no breaks versus an unknown number of breaks. The third type of tests are for the null of k breaks versus $k+1$ breaks in the model. The fourth type, which are most useful in the present context, are those that estimate any breaks sequentially. The next section presents the estimation results using these methodologies for identifying discrete and continuous breaks.

The breaks identified by the discrete-break tests outlined above can be further evaluated by employing the timing methodology of DeJong et al (2004). This method employs the maximum likelihood estimates of models, such as those above, over varying intervals of time to compute the probability of a break in any given time period. In particular, given a sample $[1,T]$ and two possible sub-samples, say, $[1,T_1]$ and $[T_2+1,T]$, DeJong et al (2004) maintain the assumption that there is a break in the intervening sample $[T_1,T_2]$. The idea then is to use likelihoods to assign probabilities of a break to particular dates in $[T_1,T_2]$, as follows. First, two likelihoods are estimated (initial and final) for $[1,T_1]$ and $[T_2+1,T]$ respectively. Then, given the fixed estimates for these two sub-samples, the procedure requires that as the sample is increased, the likelihoods be estimated again leaving free the parameters over which a break is suspected[6]. Letting $L_1(\cdot \mid \theta_1)$ and $L_1(\cdot \mid \theta_2)$ denote the initial and final likelihoods (where θ is the vector of parameters in a model M_t) and j_0 as the true unknown break-date, the conditional likelihood given the occurrence of a break at date j is,

$$L(\{M_t\} \mid j_0 = j, \theta_1, \theta_2) = L_1(\{M_t\}_{t=1}^{j} \mid \theta_1) \times L_2(\{M_t\}_{t=j+1}^{T} \mid \theta_2) \tag{3.8}$$

Given this conditional likelihood, conditional probabilities can be constructed as,

$$p(j_0 = j \mid \{M_t\}, \theta_1, \theta_2) = \frac{L(\{M_t\} \mid j_0 = j, \theta_1, \theta_2)}{\sum_{\tau=T_1+1}^{T_2} L(\{M_t\} \mid j_0 = \tau, \theta_1, \theta_2)} \tag{3.9}$$

and hence the probabilities assigned to any given break date in an interval can be computed. These probabilities, that are conditional on there being a break, can thus identify the timing of breaks with confidence intervals derived from the cumulative distribution function associated with the probabilities above.

3.3 ESTIMATION RESULTS

Table 12 in Appendix B presents the results of estimating equations (3.3) and (3.5) using Hansen's (2000) methods assuming a single break. For the backward looking model the estimated break date (1982QIV) has relatively narrow 95% confidence interval (1982QII-1983QI) and a good fit (as the joint R^2 of the model with one break at 1982QIV is 0.819). However, in these results, the pre-break estimate of α_1 is rather weak and the post-break estimate is more significant; this could be a feature of the short pre-break sample. The estimates for the mixture model are stronger in that the estimate for α_5 is significant in the overall and pre-break sample. In the post-break sample the significance of α_5's estimate falls reflecting in part the low variability of inflation expectations in that time period as

[6] The results presented in this paper are the one-shot probabilities for parametric models as per DeJong et al (2004). Estimation is carried out with the free parameter being the effect of capacity utilization on inflation (α_1); T_1 and T_2 are chosen so that the initial and final likelihoods are based on at least thirty observations.

exhibited in Figure 57 of Appendix C. The main estimation result for the mixture model is the break date of 1983QIV with a large confidence interval of 1982QII-1991QII which is suggestive of multiple breaks. Finally, Table 12 confirms a decreasing estimate of α_1 from 0.223 (pre-break) to 0.095 (post-break) with the former being the more significant estimate in the mixture model. Overall, the results presented in Table 1 suggest breaks in both the backward looking and mixture models with possibly a decreasing coefficient on capacity utilization across the breaks.

Multiple break tests following Bai & Perron (1998) are presented in Table 13 of Appendix B. The $\sup F(0|k)$ tests reject the null of breaks for the alternative of k possible breaks across the board ($k = 1$ to 5) for both the backward looking and mixture models. The same holds for the $D\max$ tests of no breaks versus the null of an unknown number of breaks. The $\sup F(k+1|k)$ tests of the null of k breaks versus the alternate of $k+1$ breaks suggest two breaks for the backward looking model and three for the mixture model. The estimation of sequential breaks finds two breaks for the backward looking model that correspond to the 1981-1982 recession and the inflation targeting regime officially instituted by the Bank of Canada in 1991QI. For the mixture model three breaks are estimated sequentially corresponding to the 1981-1982 recession, a period of time corresponding to increasing free trade and fiscal stability (1996QI-1997QII) and inflation targeting. In Canada, after the (possibly deflation induced) 1981-1982 recession, budget surpluses were reported from 1995 onwards and aside from monetary policy regime changes, the free trade process culminated in the signing of NAFTA in the late 1990's. Overall, the results suggest multiple discrete breaks in the linear relations (3.3) and (3.5) and attention can now be turned towards identifying any continuous breaks.

Table 14 in Appendix B along with Figures 4-6 in Appendix C provide the results of time-varying parameter estimation following Kim & Nelson (1999). In the estimation diffuse priors were assumed for the initial values and a time-varying approach was validated by the Breusch-Pagan LM tests reported in Table 14[7]. Figure 59 plots the time-varying parameter

[7] Whereas the LM test clearly supports a time-varying approach for the backward looking model, the test for the mixture model is marginally supportive.

$\widehat{\alpha}_{1t}$ for both models and clearly demonstrates the decreasing effect of capacity utilization on inflation. Further, Figures 60 and 61 suggest that the introduction of survey expectations reduces the variance of the specification while leaving the forecast errors relatively unaffected[8]. It is of importance to note that alternate priors for the initial values lead to qualitatively similar results, namely a decreasing $\widehat{\alpha}_{1t}$ for both models albeit with different standard error estimates for the time-varying parameters. However, Kim & Nelson (1999) note that when β_t evolves as specified in (3.7), the initial values in the Kalman Filter can be set to an arbitrary value with large initial uncertainty, hence the diffuse prior results are reported in Table 14 and in Figures 59-61.

Finally, Figures 62-63 present the one-shot probabilities computed using the DeJong et al (2004) methodology. Figure 62 presents the results from estimating both the backward looking model and the mixture model assuming that the errors in equations (3.3) and (3.5) are not autocorrelated; the results in Figure 63 allow for autocorrelation. As can be seen in the plots, the highest probabilities of breaks are assigned in the late 1980's and early 1990's.

Overall the results suggest discrete breaks along with a continuous deterioration in the utilization-inflation relationship. In addition the data prefer a model that incorporates forward looking behavior. Finally, the results can be interpreted within the context of recent Canadian economic history. This history can be summarized by three main economic events: deflation and inflation targeting, fiscal stability and the process of free trade. After the excesses of the 1970's, the Bank of Canada was committed to a transparent monetary policy that ensured low and stable inflation. This commitment resulted in the initial deflation of the 1980's and the subsequent move to inflation targeting. Indeed, Longworth (2002) outlines the resulting benefits stemming from reduced inflation uncertainty.

> "The reduced uncertainty about inflation seems to have had a number of significant benefits. First, it seems to have led to a decline in relative wage variability because of less disagreement about the inflation outlook, therefore leading to a better allocation of labour. Second, it certainly has made planning easier and has led to longer labour and financial contracts, which means lower transactions and bargaining costs for firms and households. Third, it has likely been an important factor in a reduction of days lost to

[8] In addition, given the results in Table 14, the null hypothesis that survey expectations are not significant can be rejected with a likelihood ratio test.

> labour disruptions. Fourth, it means that there is less need to protect oneself against unexpected inflation, which is a real saving of resources. Fifth, it has been a factor leading to the development of more complete financial markets (with longer-term instruments), which allows a greater diversification of risks at lower cost. Finally, it has been associated with less variable interest rates, which, in turn, have led to lower capital losses and gains on bonds, and have tended to lead to lower risk premiums on longer-term instruments."

These benefits can be clearly interpreted as having decreased the degree of nominal rigidity. In addition, fiscal stability can lead to a better allocation of resources due to reduced uncertainty about aggregate fiscal policies. Such stability was obtained by a move to eliminate high deficits, surpluses were indeed finally reported in the mid-1990's. This result was accomplished with a mixture of reduced taxes and cuts in spending.

Finally, the process of free trade should decrease the significance of cost-push shocks as firms compete to satisfy aggregate demand. For Canada, free trade not only opened the vast markets of the United States but also led to increased competitive pressures from firms in the United States. It would therefore seem that a reasonable conjecture is that these increased competitive pressures and decreased rigidities should lead to an uncoupling between a real resource utilization measure and inflation.

In order to verify this conjecture, a model is required that predicts a relationship between capacity utilization and inflation due in part to nominal rigidities and cost-push pressures. That is, the model must capture the intuition outlined in the Introduction (as adapted from Shapiro (1989)). Given such an environment, empirical evaluation of the model must show that an uncoupling between real resource utilization and inflation may occur if the significance of cost-push shocks decreases relative to 'fundamental' shocks such as technology and demand shocks. Such an environment is provided within the New Keynesian literature that allows for cost-push shocks to compete with 'fundamental' shocks in the data; in addition the literature is able to account for both backward looking and forward looking behavior. The next section describes one such model and evaluates it empirically to lend credence to the above conjecture.

3.4 MONOPOLISTIC COMPETITION AND CAPACITY UTILIZATION

The previous section documented that free trade, fiscal stability and changes in monetary policy regimes may have had an effect on the capacity utilization-inflation relationship. In particular these institutional changes can be interpreted as mapping into increased competition and decreased rigidities in the economy. This section outlines a model of imperfect competition with sticky prices, and then estimates the model in order to possibly lend credence to this conjecture. The model is provided by Ireland (2003) and is indeed a standard in the literature.

3.4.1 THE BASIC ENVIRONMENT

The aggregate economy, operating in discrete time, is assumed to consist of a representative household, a finished goods firm, a continuum of intermediate inputs firms and a central bank. The intermediate inputs firms each produce a differentiated output used in the production of the final good. The details of the basic environment are as follows.

3.4.1.1 HOUSEHOLDS Households are assumed to maximize utility defined over consumption, money and the disutility of labor. The representative household's optimization objective is given by,

$$Max. \qquad U = E_0 \sum_{0}^{\infty} \beta^t \left\{ a_t \log C_t + \log \frac{M_t}{P_t} - \frac{N_t^{\eta}}{\eta} \right\} \tag{3.10}$$

$$s.t. \qquad P_t C_t + \frac{B_t}{R_t} + M_t = M_{t-1} + B_{t-1} + T_t + W_t N_t + D_t \tag{3.11}$$

$$\beta \in (0,1), \qquad \eta \geq 1 \tag{3.12}$$

In the specification of the budget constraint (3.11) above, it is assumed that the household holds bonds (B) and money (M), where the former matures at a gross nominal rate of R_t between two discrete time periods. The household also receives transfers (T) from the monetary authority and works (N) in order to earn wages (W) to meet its' expenditures.

Finally, the household is assumed to own the intermediate inputs firms and thus receives a dividend payment from the firms in each period (D). The solution to the households problem yields a demand for money balances, supply of labor and a demand for the final consumption good, as follows,

$$\frac{M_t}{P_t} = \frac{C_t R_t}{a_t(R_t - 1)} \tag{3.13}$$

$$C_t N_t^{\eta-1} = \frac{a_t W_t}{P_t} \tag{3.14}$$

$$\beta E_t \left\{ \frac{a_{t+1}}{P_{t+1} C_{t+1}} \right\} = \frac{a_t}{P_t C_t R_t} \tag{3.15}$$

These first order conditions along with the budget constraint are the first in a system of equations that will characterize the aggregate economy.

3.4.1.2 FIRMS There are two types of firms, one that produces a final consumption good and a continuum of intermediate inputs firms that supply inputs to the final consumption good firm. The final good firm is assumed to operate in a competitive environment and thus solves the following static problem,

$$Max. \qquad \Pi_t^F = P_t Y_t - \int_0^1 P_{it} Y_{it} di \tag{3.16}$$

$$s.t. \qquad Y_t = \left\{ \int_0^1 Y_{it}^{\frac{\theta_t - 1}{\theta_t}} di \right\}^{\frac{\theta_t}{\theta_t - 1}} \tag{3.17}$$

where (3.17) is the production function for the final good firm. The solution to the final good firms' problem yields the standard demand for intermediate inputs and the price aggregator,

$$Y_{it} = Y_t \left\{ \frac{P_{it}}{P_t} \right\}^{-\theta_t} \tag{3.18}$$

$$P_t = \left\{ \int_0^1 P_{it}^{1-\theta_t} di \right\}^{\frac{1}{1-\theta_t}} \tag{3.19}$$

The intermediate firms are assumed to be monopolistically competitive and since each is assumed to produce a distinct perishable good such that firm i produces good i, the analysis focuses on one such representative firm. This type of firm is assumed to be owned by the household and thus it maximizes the real value of the dividend to the household. Further, as is typically the case, it is the specification of this particular portion of the environment that generates Phillips curves. Assuming that these firms face a quadratic adjustment cost of changing prices suffices[9], and thus the intermediate firm's optimization problem is,

$$Max. \qquad \Pi_{it}^{I} = E_0 \sum_{0}^{\infty} \beta^t \frac{a_t}{C_t} \left\{ \frac{P_{it} Y_{it} - W_t N_t}{P_t} - c(P_{it}, P_{it-1}) \right\} \tag{3.20}$$

$$s.t. \qquad Y_{it} = Z_t N_{it} \tag{3.21}$$

$$Y_{it} = Y_t \left\{ \frac{P_{it}}{P_t} \right\}^{-\theta_t} \tag{3.22}$$

$$c(P_{it}, P_{it-1}) = \frac{\phi}{2} \left[\frac{P_{it}}{\pi P_{it-1}} - 1 \right]^2 Y_t, \qquad \phi > 0 \tag{3.23}$$

The solution to the intermediate firms' problem yields,

$$\begin{aligned} 0 = & \frac{\theta_t}{1-\theta_t} \left(\frac{P_{it}}{P_t} \right)^{\frac{1}{\theta_t - 1}} \frac{Y_t a_t}{P_t C_t} + \frac{a_t}{1-\theta_t} \left(\frac{P_{it}}{P_t} \right)^{\frac{\theta_t}{\theta_t - 1}} \frac{W_t}{P_t} \frac{Y_t}{Z_t} \frac{1}{P_t C_t} \\ & - \phi \left[\frac{P_{it}}{\pi P_{it-1}} - 1 \right] \frac{Y_t a_t}{\pi P_{it-1} C_t} + \beta \phi E_t \left(\frac{a_{t+1}}{a_t} \left(\frac{P_{it}}{\pi P_{it-1}} - 1 \right) \frac{Y_t P_{it+1}}{\pi P_{it} P_{it}} \right) \end{aligned} \tag{3.24}$$

as the first order condition in which price dynamics are induced by the assumed degree of nominal rigidity (ϕ).

[9] Alternatives to 'sticky-prices are available, for instance, the assumption of Calvo contracts. Since the objective is to write down an empirical model, the assumption of Rotemberg (1982) style costs of nominal adjustment suffice.

3.4.1.3 STOCHASTIC ASSUMPTIONS AND EQUILIBRIUM CONDITIONS

There are three types of shocks in this economy, namely, demand shocks, technology shocks and cost-push shocks. Demand shocks (a_t), technology shocks (Z_t) and cost-push shocks (θ_t) are assumed to all have steady state values a, z and θ that are larger than unity. All shocks are assumed to evolve as per the following logarithmic processes.

$$\log(a_t) = (1-\rho_a)\log(a) + \rho_a \log(a_{t-1}) + \varepsilon_{at}, \quad a > 1 \tag{3.25}$$

$$\log(Z_t) = \log(z) + \log(Z_{t-1}) + \varepsilon_{zt}, \quad z > 1 \tag{3.26}$$

$$\log(\theta_t) = (1-\rho_\theta)\log(\theta) + \rho_\theta \log(\theta_{t-1}) + \varepsilon_{\theta t}, \quad \theta > 1 \tag{3.27}$$

Equilibrium in this model is characterized by symmetry,

$$Y_{it} = Y_t, \quad N_{it} = N_t, \quad P_{it} = P_t, \quad D_{it} = D_t \tag{3.28}$$

Money and bond markets clear so that,

$$M_t = M_{t-1} + T_t \tag{3.29}$$

$$B_t = B_{t-1} = 0 \tag{3.30}$$

The only remaining required features of the model are a Taylor rule, to represent the activities of the central bank, and a specification for capacity utilization.

3.4.2 CAPACITY UTILIZATION

Capacity utilization is typically defined to be the ratio of actual to capacity output ($\overline{Y}_t$, see Shapiro(1989)). Here capacity output is defined to be the efficient level of output, which is equivalent to claiming that it would be the level of output chosen by a benevolent social planner who would solve,

$$Max. \qquad U = E_0 \sum_0^{\infty} \beta^t \left\{ a_t \log \overline{Y}_t - \frac{1}{\eta} \left(\int_0^1 N_{it} di \right)^{\eta} \right\} \tag{3.31}$$

$$s.t. \qquad \overline{Y}_t = Z_t \left(\int_0^1 N_{it}^{\frac{\theta_t - 1}{\theta_t}} di \right)^{\frac{\theta_t}{\theta_t - 1}} \tag{3.32}$$

The solution to the problem yields an expression for capacity output implying that another equation can be added to the system so far, namely the specification of capacity utilization,

$$U_t = \frac{Y_t}{a_t^{\frac{1}{\eta}} Z_t} \tag{3.33}$$

The definition of capacity utilization here is very similar to the definition of an output gap, indeed the two are the same in this environment. In order to ensure that this is a reasonable specification, Figure 58 in Appendix C plots the two series and as can be seen in the figure, there is very little difference between the ratio (U_t) and the difference (the output gap)[10] measures.

[10] The output gap series was obtained from the Bank of Canada for the time period 1975QI-2002QIV.

3.4.3 THE EQUILIBRIUM SYSTEM

The equilibrium system consists of the first order conditions of the household, its' budget constraint, the aggregate production function having imposed symmetry, the aggregate real dividends from the intermediate input firms to the households and the first order condition of the intermediate inputs firms. The system can be normalized by Z_t and wages, money, labor, dividends and capacity output can be eliminated. The steady states of those variables not specified exogenously are given by,

$$R = \frac{z\pi}{\beta}, \quad C = Y = \left(a\frac{\theta - 1}{\theta}\right)^{\frac{1}{\eta}}, \quad U = \left(\frac{\theta - 1}{\theta}\right)^{\frac{1}{\eta}} \tag{3.34}$$

Employing these steady states in log-linearizing the system yields the following form,

$$a_t = \rho_a a_{t-1} + \varepsilon_{at}, \quad \varepsilon_{at} \sim NID(0, \sigma_a^2), \quad |\rho_a| < 1 \tag{3.35}$$

$$u_t = y_t - \omega a_t, \quad \omega = \eta^{-1} \tag{3.36}$$

$$u_t = \alpha_x u_{t-1} + (1 - \alpha_x) E_t u_{t+1} - (r_t - E_t \pi_{t+1}) + (1 - \omega)(1 - \rho_a) a_t, \quad \alpha_x \in [0, 1] \tag{3.37}$$

$$\theta_t = \rho_\theta \theta_{t-1} + \varepsilon_{\theta t}, \quad \varepsilon_{\theta t} \sim NID(0, \sigma_\theta^2), \quad |\rho_\theta| < 1 \tag{3.38}$$

$$\pi_t = \beta \alpha_\pi \pi_{t-1} + \beta(1 - \alpha_\pi) E_t \pi_{t+1} + \frac{\eta(\theta - 1)}{\phi} u_t - \frac{1}{\phi}\theta_t, \quad \alpha_\pi \in [0, 1] \tag{3.39}$$

$$g_t = y_t - y_{t-1} + z_t \quad \rightarrow g = z \tag{3.40}$$

$$z_t = \varepsilon_{zt}, \quad \varepsilon_{zt} \sim NID(0, \sigma_z^2) \tag{3.41}$$

$$r_t = \rho_r r_{t-1} + \rho_\pi \pi_t + \rho_g g_t + \rho_u u_t + \varepsilon_{rt}, \quad \varepsilon_{rt} \sim NID(0, \sigma_r^2) \tag{3.42}$$

where all variables are in log deviations from their steady states, that is, $x_t = \log(X_t) - \log(X)$ where X is the steady state value of the variable X_t. Equations (3.35), (3.38) and (3.41) describe the shock processes for demand, cost-push and technology shocks respectively. Equation (3.37) is the familiar IS curve, and equation (3.39) is the forward looking Phillips curve. Finally, equation (3.42) is the Taylor rule followed by the central bank. Here it is assumed that the Bank of Canada reacts to inflation, the observable growth rate of output (g_t) and capacity utilization. In addition, the above model can be simplified by letting the cost-push shock be defined as $e_t = \frac{1}{\phi}\theta_t$ implying that $\rho_e = \rho_\theta$ and $\sigma_e = \frac{1}{\phi}\sigma_\theta$. Finally, setting $\alpha_x = \alpha_\pi = 0$ yields the original micro-foundations, since lagged inflation terms typically have an influence, these additional parameters have been introduced.

The main conjecture in this chapter is that the aggregate Canadian economy has become increasingly competitive after 1984QII, and that the economy may also be facing reduced nominal rigidities after that break as well[11]. Within the context of the model above, demonstrating the validity of this conjecture translates into demonstrating that the steady state price mark-up $\left(\frac{1}{\theta-1}\right)$ and ϕ have decreased conditional upon any changes in the curvature of the disutility of labor function as measured by η; given that the influence of utilization on inflation is given by $\psi = \frac{\eta(\theta-1)}{\phi}$ in the Phillips curve. Thus, maximum likelihood methods are employed in the next section to estimate the parameters.

Finally, it is instructive to note that the definition of capacity utilization above is different from that typically assumed in the literature. The analysis of capacity utilization as a propagation tool has received attention from several researchers. Wen (1998) builds a real business cycle model with a depreciation-in-use definition of capacity utilization in order to demonstrate that the resulting propagation mechanism is sufficient to explain several aspects of the U.S. business cycle. Unlike Wen (1998), in this chapter capacity utilization is defined as the ratio of choices under decentralized and social planner problems, with the result that capacity utilization moves in response to technology and demand shocks. The depreciation-in-use assumption is also evaluated by Fagnart et al. (1999) in a model with imperfect markets. They focus on the difference between capacity utilization and capital utilization. In their economy monopolistic firms use putty-clay technologies and react to demand shocks. As a result they are able to demonstrate that some firms may idle and why utilization rates may differ across firms. The analysis in this chapter can therefore be interpreted as being complementary to those of Wen (1998) and Fagnart et al. (1999). The main difference being that here an explicit characterization with respect to market structure is being sought as the conjecture is that increased competition, all things equal, will lead this variable to

[11] This date corresponds to the endpoint of the 95% confidence interval of the first break in the mixture model noted in Table 13.

potentially lose its' link with inflation. Indeed Corrado & Mattey (1997) discuss the link between capacity utilization and inflation for the United States in detail. They outline the explanations behind the link between high capacity utilization and inflation, and also provide a discussion of the practicalities of the measurement of this statistic for the United States. However, in Canada, the transmission of high capacity utilization to inflation may be breaking down, using aggregate data benchmarked to surveys which provides a unique inflationary indicator.

3.5 MODEL EVALUATION

The model in the previous section could conceivably be simulated given calibrated values for parameters. However, assuming values for the parameters of the Taylor rule can be a questionable proposition. This is in part due to the instability of the Taylor rule in general, and in the Canadian context there does not seem to be a consensus on its' parametrization. Therefore, parameter estimates are obtained from the data.

3.5.1 ECONOMETRIC SPECIFICATION

The above model can be written as the following system of linear stochastic difference equations.

$$\xi_t \equiv [y_{t-1} \quad r_{t-1} \quad \pi_{t-1} \quad g_{t-1} \quad u_{t-1} \quad \pi_t \quad u_t]' \tag{3.43}$$

$$v_t \equiv [a_t \quad e_t \quad z_t \quad \varepsilon_{rt}]' \tag{3.44}$$

$$AE_t\xi_{t+1} = B\xi_t + Cv_t \tag{3.45}$$

where the matrices A, B and C have as elements the parameters as they appear in the system (3.35)-(3.42). Given this structural form a method is needed to solve the system of linear stochastic difference equations in terms of the parameters; the solved system could then be used to calibrate or estimate the parameters. This particular structural form can be solved using a Schur decomposition; the solved structural system is,

$$\zeta_t \equiv [y_{t-1} \quad r_{t-1} \quad \pi_{t-1} \quad g_{t-1} \quad u_{t-1} \quad a_t \quad e_t \quad z_t \quad \varepsilon_{rt}]' \tag{3.46}$$

$$\varepsilon_t \equiv [\varepsilon_{at} \quad \varepsilon_{et} \quad \varepsilon_{zt} \quad \varepsilon_{rt}]' \tag{3.47}$$

$$\zeta_{t+1} = \Pi(\Lambda)\zeta_t + \Delta\varepsilon_{t+1}, \quad \Delta = \left[\underset{(5\times4)}{0}, \quad \underset{(4\times4)}{I} \right]' \tag{3.48}$$

where Π is a matrix containing the parameters of the model and comes from combinations of the matrices A, B and C. Finally, the vector Λ represents the deep parameters of interest.

In the system represented by (3.48), certain variables are unobserved and others are observed. In particular it is not possible to observe an underlying cost-push shock process and thus filtering methods are required in order to form statistical inference on parameters which is the goal of the exercise. For this purpose Kalman Filtering is employed widely in the literature and is used in the present analysis. The Kalman Filter requires a state-space representation that links observables to unobservables. The observables (per capita output growth, inflation and real interest rates) are denoted as[12],

$$\gamma_t \equiv [g_t \quad \pi_t \quad r_t]' \tag{3.49}$$

The state-space representation of the model is therefore,

$$\zeta_{t+1} = \Pi(\Lambda)\zeta_t + \Delta\varepsilon_{t+1} \tag{3.50}$$

$$\gamma_t = \Gamma(\Lambda)\zeta_t \tag{3.51}$$

$$\Sigma = E(\varepsilon_t\varepsilon_t') = diag(\sigma_a^2, \sigma_e^2, \sigma_z^2, \sigma_r^2) \tag{3.52}$$

$$\Gamma(\Lambda) = [\Pi(\Lambda)_4 \quad \Pi(\Lambda)_3 \quad \Pi(\Lambda)_2]' \tag{3.53}$$

which yields a log-likelihood function $\log L(\Lambda)$, the subscripts 4, 3 and 2 denote the corresponding rows of Π, the reduced form matrix. However, the model is difficult to identify partly because $\sigma_e = \frac{1}{\phi}\sigma_\theta$ enters the variance-covariance matrix of the state system. Indeed, it

[12] Data were obtained from Cansim on real GDP (series v1992067), the implicit price deflator (series v1997756), population (series v1) and the 3-month Canadian Treasury bill rate (series v122531).

is well-known that such estimation may be plagued by identification problems (see Hamilton (1994)). Therefore, the next section presents estimates for various versions of the model in order to evaluate the conjectures[13].

3.5.2 ESTIMATION RESULTS

In the model described above a link between utilization and inflation exists in so far as the cost-push shock process is in operation and the degree of nominal rigidities is significant. Indeed, the New Keynesian literature estimates the above model assuming a steady state mark-up of 20% ($\theta = 6$) and a level of rigidity given by $\phi = 50$, which corresponds to goods prices being reset a little more than once per year. However, given the estimation results of the backward looking and mixture models, the main conjecture is that the relative importance of cost-push shocks and the degree of rigidity is diminishing, thus causing an uncoupling of inflation from capacity utilization. Therefore, the inferential focus in this section is on the estimates of ρ_θ (ρ_e), σ_θ (σ_e) and ϕ, in one form or another. In addition, given the identification issue discussed above, several versions of the model were estimated in order to ascertain whether the conjectures holds, albeit if qualitatively.

Table 15 in Appendix B presents the baseline estimation results having fixed the values of θ and ϕ to conventional levels[14]. The results suggest a large estimate of η across the three time periods (full sample, pre-break and post-break). This is due to a low estimated ω which is required for the demand shocks to have a strong influence, the data clearly prefer significant demand shocks. Further, forward looking behavior is witnessed by the estimates of α_x and α_π which are near zero across the samples. However, the main result of interest in Table 4 is that after the break, the estimates of ρ_e and σ_e fall suggesting that even with calibrated rigidities and a steady-state mark-up, the role of cost-push shocks is diminishing.

[13] In an earlier version of this paper, a two-step maximum likelihood procedure was employed that fixed the values of θ and ϕ to obtain estimates of the remaining parameters, and then conditional upon those estimates the likelihood was maximized again with respect to θ and ϕ. In a still earlier version, a simulated method of moments procedure following Gourieroux et al. (1993) was employed. In both of these versions the results were qualitatively the same as those reported here.

[14] The value of β was held fixed at 0.99 in all of the results presented in this section.

Next, in order to verify whether the influence of utilization on inflation is diminishing, the composite parameter ψ is included in the list of estimated parameters. The results in Table 16 of Appendix B suggest a decreasing estimate of ψ and ρ_e, however the estimate of σ_e increases in the post-break sample. In this model the cost-push shocks compete with technology and Taylor rule shocks, and it seems that some of the variation is captured by σ_e, however the autoregressive parameter ρ_e is insignificant. Finally, both Tables 15 and 16 suggest the Taylor rule be modelled in differenced form as the estimates of ρ_r across samples are near unity.

Table 17 of Appendix B presents the estimation results when θ and ϕ are included in the list of estimated parameters with a Taylor rule in differenced form. The results suggest a decreasing mark-up from 40% to 12%; however even though a decrease is observed across the break in the estimate of ϕ, the pre- and post-break estimates are not statistically different from one another. In addition Table 17 suggests a much larger post-break estimate of ρ_θ and σ_θ than in Tables 15 and 16, which is to be weighed against the fact that the likelihoods of the model are significantly different, and that the estimate of σ_θ is still dominated by the estimate of σ_z.

Overall, the estimation results suggest that at the very least the influence of the cost-push shock may be disappearing, which suggests increasingly competitive behavior. Next, the model estimates suggest, albeit to a much smaller extent, that the role of nominal rigidities may also be diminishing. Finally, the model estimates suggest a strong role for demand and technology shocks and that forward-looking behavior may be prevalent in the data. Taken as a whole it would seem that, conditional upon the activities of the Bank of Canada as represented by a Taylor rule, a better characterization of the Canadian economy may be one that has flexible prices and competitive market structures. Indeed, the model estimates presented here along with recent Canadian economic history, summarized above, may suggest a move towards a real business characterization. Such a transition would not only imply a change in the sort of shocks that drive the business cycle but perhaps also aggregate economic policy.

3.6 CONCLUSION

In recent years high capacity utilization levels have existed without corresponding increases in inflation. In Canada aggregate capacity utilization rates are based on business surveys, thereby making the Canadian case of high utilization-low inflation of particular interest. This chapter first determined some stylized facts about the relationship in recent years, namely that there are breaks over time in the relationship and that at the very least utilization has a decreasing effect on inflation through time. Given these facts, the conjecture that a move towards increasingly competitive market structures and flexible prices may have caused a deterioration in the relationship, was explained and evaluated within a New Keynesian general equilibrium model.

This chapter is part of an emerging trend in the New Keynesian literature, that of attempting to model jointly the advantages offered by 'efficient' shocks (that is, shocks to demand and technology) in New Classical models and the advantages afforded by recognizing non-Walrasian features of real world environments, such as those offered in this chapter. Indeed in the inventive interpretation of the discussion in Clarida et al. (2000), Ireland (2003) demonstrates that cost-push shocks are as, if not more, important than technology shocks in explaining the joint behavior of U.S. output, inflation and interest rates. In that chapter, a version of the above model is estimated to demonstrate that the link between New Keynesian model environments and real business cycle models is slowly disintegrating, and a new modeling paradigm emerging. The current analysis demonstrates an application of this new emerging paradigm, an instance in which the Canadian economy may be tending away from New Keynesian assumptions and towards characterizations provided by real business cycles.

Finally, the analysis presented above could benefit from two particular extensions. The first would include a richer specification for capital utilization following Greenwood et al. (1988), possibly within the context of a small open economy. The main motivation for a richer specification of the production technology would be to allow for increased realism with respect to variable capital utilization interacting with technology and cost-push shocks. An open economy model may also be more suitable for the Canadian case. However this may not prove to be of much interest given the exchange rate disconnect puzzle[15] and the fact that Clarida et al. (2000) find that, qualitatively, the solutions to various monetary-policy design problems for the closed economy carry over to an open economy. Second, the analysis may benefit from a richer role for the monetary authority as an institution who changes from discretion to a rules based approach. These issues are left for continuing research that would examine more closely the evolution of competitive market structures and flexible prices.

[15] See Obstfeld & Rogoff (2000).

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APPENDIX A

EXPERIMENT INSTRUCTIONS

There are two sets of balls that we will use in this experiment. This set has 7 black balls and 3 white balls – we call this set of balls “more black”. This other set has 3 black balls and 7 white balls - we call this set of balls “more white”. This experiment will last for 6 rounds. Before we begin each round, we will randomly select one set to be used in that round. We will place each set in a bag, and then put both bags into this box. We will shake the box to mix up the bags, then select one of the bags. We will pour that set of balls into the covered bingo cage. Both sets have an equal chance to be selected.

Once the set of balls is placed in the bingo cage, you will fill in the first line of the chart on your record sheet that says, “I think the chance that the bingo cage contains “more black” is ___ % and the chance that it contains “more white” is ___ %”. Since the “more black” and “more white” sets are the only possibilities, your two numbers should add up to 100%. Then, we will draw one ball from the bingo cage and announce what color it is. On the line for “Draw #1” on your record sheet, you should circle the color of the ball and then fill in the chance percentage boxes in that line. After everyone has recorded his or her answers, we will replace the ball in the bingo cage and draw again. There will be 10 draws in each round. At the end of the round, we will uncover the bingo cage to reveal which set of balls was used.

First, to practice, we will demonstrate the drawing procedure in person here in the front of the room. For the actual experiment, you will see a videotape of the same procedures, which we recorded earlier.

After all 6 rounds have been completed, we will calculate your payment. You will be paid $5 for attending the experiment. In addition you have the opportunity to win a $10 bonus payment, based on the chance numbers you reported during the experiment. At the end of the experiment, we will choose one draw from one round to determine the bonus bet. There are two bets you may play to win the bonus payment: the “Dice Bet” or the “Ping Pong Ball Set Bet”. You will play whichever bet has the greater chance of winning for you.

For the “Dice Bet”, we will randomly select a “Lucky Number” from 51 to 100 from a set of numbered balls in the bingo cage. Then we will roll 2 ten sided dice to get a number from 1 to 100. If the number rolled on the dice is less than or equal to the “Lucky Number” then you win the bonus payment. The chances of winning this bet are exactly the value of the Lucky Number. For example, if the Lucky number is 75, then you win the bonus payment if we roll a number from 1 to 75, and lose if we roll a number from 76 to 100. Therefore you have exactly a 75% chance of winning this bet.

For the “Ping Pong Ball Set Bet”, the computer will randomly select a round and draw from the experiment to determine your payment. If you correctly predicted which set of ping pong balls were used in that round, you will win the bonus payment. For example, if in the selected round and draw, you had entered the chance for the set being the “More Black Set” as 80% and the “More White Set” as 20%. Then if the set was actually the “More Black Set” you win the bonus payment and if the set was actually the “More White Set” you lose.

Note that you have the best chance of winning the bonus prize if you write down the most accurate chance percentages in each round that you can. This will guarantee that you will play the bet with the highest probability of winning the bonus payment.

There is to be no talking during the experiment. If you have any questions about how this experiment works, please ask the experimenter.

APPENDIX B

TABLES

Table 1: Summary Statistics (Thousands of Dollars)

		Mean	Std. Dev.	Min.	Max.
y_{it}	Overall	4303	7904	1	70892
	Between		7234	6	51240
	Within		3195	-18077	41357
x_{it}	Overall	3864	7168	2	63181
	Between		6667	8	48124
	Within		2642	-14937	38996
ε_{it}	Overall	440	2895	-22716	24178
	Between		1520	-10549	10342
	Within		2464	-20875	22892
z_{it}	Overall	52707	80329	443	1335897
	Between		77578	710	980118
	Within		21001	-439344	408486
	N	775			
	T	7			

Table 2: Yearly Correlations

1987	y_i	x_i	ε_i	$z_{i,-1}$	1988	y_i	x_i	ε_i	$z_{i,-1}$
y_i	1				y_i	1			
x_i	0.92	1			x_i	0.93	1		
ε_i	0.23	-0.15	1		ε_i	0.29	-0.07	1	
$z_{i,-1}$	0.65	0.61	0.14	1	$z_{i,-1}$	0.64	0.59	0.19	1
1989	y_i	x_i	ε_i	$z_{i,-1}$	1990	y_i	x_i	ε_i	$z_{i,-1}$
y_i	1				y_i	1			
x_i	0.93	1			x_i	0.94	1		
ε_i	0.45	0.10	1		ε_i	0.58	0.29	1	
$z_{i,-1}$	0.63	0.62	0.22	1	$z_{i,-1}$	0.59	0.59	0.26	1
1991	y_i	x_i	ε_i	$z_{i,-1}$	1992	y_i	x_i	ε_i	$z_{i,-1}$
y_i	1				y_i	1			
x_i	0.93	1			x_i	0.91	1		
ε_i	0.51	0.16	1		ε_i	0.35	-0.06	1	

Table 3: Overall Correlations

	y_{it}	x_{it}	ε_{it}	z_{it-1}	y_{it-1}	x_{it-1}	ε_{it-1}
y_{it}	1						
x_{it}	0.93	1					
ε_{it}	0.43	0.07	1				
z_{it-1}	0.62	0.60	0.20	1			
y_{it-1}	0.88	0.86	0.28	0.60	1		
x_{it-1}	0.89	0.90	0.20	0.59	0.93	1	
ε_{it-1}	0.23	0.14	0.28	0.18	0.44	0.09	1

Table 4: Estimation Results I (Estimates)

Equation -Method	α_0	α_1	α_2	α_3	α_4	$\lvert m_1\rvert, \lvert m_2\rvert$	R^2
		Coefficients				Test Statistics	
(1.4)-OLS	431.543	0.447		0.530			
	(112.100)	(0.055)		(0.061)			0.82
(1.4)-Within	..	0.070		0.313			
	..	(0.055)		(0.066)			0.12
(1.4)-GMM	608.094	0.349		0.486		$6.64, 1.55$	
	(321.100)	(0.069)		(0.096)		$S = 521.5$	0.80
(1.9)-OLS	279.625	0.413	0.576	-0.086	0.002		
	(78.340)	(0.039)	(0.034)	(0.038)	(0.001)		0.89
(1.9)-Within	..	-0.019	0.504	0.039	0.010		
	..	(0.038)	(0.036)	(0.034)	(0.003)		0.40
(1.9)-GMM	193.287	0.271	0.627	-0.071	0.010	$8.38, 0.17$	
	(165.700)	(0.067)	(0.071)	(0.047)	(0.004)	$S = 536.1$	0.88
(1.13)-OLS	167.525	0.254			-0.005		
	(114.000)	(0.047)			(0.002)		0.10
(1.13)-Within	..	-0.034			-0.009		
	..	(0.046)			(0.006)		0.02
(1.13)-GMM	1.296	0.214			-0.001	$8.49, 0.28$	
	(217.100)	(0.059)			(0.003)	$S = 367.6$	0.08
(1.16)-OLS	0.216	0.110			0.002		
	(0.121)	(0.057)			(0.001)		0.08
(1.16)-Within	..	-0.109			0.002		
	..	(0.054)			(0.001)		0.03
(1.16)-GMM	0.239	-0.061			0.002	$1.55, 0.09$	
	(0.148)	(0.035)			(0.001)	$S = 271.7$	0.05

Table 5: Estimation Results I (Hypothesis Tests)

Equation	F^*	F at .95	Accept H_0?
(1.4)-OLS	1.38	3.84	Yes
(1.4)-Within	174.58	3.84	No
(1.4)-GMM	7.22	3.84	No
(1.9)-OLS	117.11	2.37	No
(1.9)-Within	351.62	2.37	No
(1.9)-GMM	43.68	2.37	No
(1.13)-OLS	25.65	3.00	No
(1.13)-Within	1.76	3.00	Yes
(1.13)-GMM	6.44	3.00	No
(1.16)-OLS	29.96	3.00	No
(1.16)-Within	8.93	3.00	No
(1.16)-GMM	7.38	3.00	No

Table 6: Estimation Results II

Equation	Coefficients				Test Statistics		
	α_0	α_1	α_2	α_3	ρ	$B-W$	F^*, R^2
(1.18)	300.881	-0.666		0.596	0.211	2.07	$F^* = 64.98$
	(137.212)	(0.019)		(0.021)			$R^2 = 0.18$
(1.20)	15.684		0.653	0.176	0.129	2.12	$F^* = 791.04$
	(97.860)		(0.009)	(0.009)			$R^2 = 0.87$
(1.22)	625.970		0.784		0.143	2.04	$F^* = 667.22$
	(95.510)		(0.006)				$R^2 = 0.87$

Table 7: Estimation Results III

	Global		Regime 1: $z_t < \$104m$		Regime 2: $z_t \geq \$104m$	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Shipment Threshold:						
β_0	231.206	35.411	333.195	34.027	1119.092	262.491
β_1	0.844	0.012	0.750	0.018	0.841	0.019
(R^2, N)	(0.87, 5425)		(0.78, 4703)		(0.80,722)	
Threshold Estimate 95% C.I.:			($\$100.02m - \$113.41m$)			
Absolute Forecast Error Threshold:						
			Regime 1: $\lvert \mathbf{x}_t - \mathbf{y}_t \rvert < \$10.49m$		Regime 2: $\lvert \mathbf{x}_t - \mathbf{y}_t \rvert \geq \$10.49$	
β_0	231.206	35.411	47.135	24.935	10763.94	1989.78
β_1	0.844	0.012	0.897	0.009	0.462	0.052
(R^2, N)	(0.87, 5425)		(0.91,5313)		(0.29, 112)	
Threshold Estimate 95% C.I.:			($\$10.27m - \$11.02m$)			

Table 8: Equation (2.10) Estimation Results

	Treatment A			Treatment B			Treatment C		
	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$
α_0	0.326	0.027	11.960	0.208	0.018	11.410	0.281	0.031	9.010
α_1	0.805	0.041	19.450	0.764	0.034	22.800	0.919	0.037	24.750
α_2	0.117	0.048	2.450	0.058	0.034	1.710	0.181	0.052	3.520
α_3	-0.486	0.056	8.620	-0.371	0.038	9.720	-0.504	0.059	8.530
α_4	-0.239	0.052	4.590	0.003	0.043	0.070	-0.289	0.061	4.710
α_5	0.109	0.053	2.050	0.183	0.040	4.590	-0.023	0.044	0.510
N	23			29			20		
R^2	0.576			0.542			0.674		
H_0^F	(4.400, 0.000)			(3.260, 0.000)			(1.830, 0.016)		
H_0^1	(181.000, 0.000)			(57.330, 0.000)			(159.480, 0.000)		
H_0^2	(12.330, 0.000)			(21.81, 0.000)			(7.400, 0.001)		

Table 9: Equation (2.22) Estimation Results

	Treatment A			Treatment B			Treatment C		
	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$
β_0	0.292	0.026	11.200	0.205	0.018	11.530	0.256	0.030	8.610
β_1	0.703	0.042	16.690	0.732	0.034	21.570	0.844	0.037	22.900
β_{21}	0.096	0.046	2.070	0.032	0.034	0.930	0.138	0.048	2.900
β_{22}	0.330	0.063	5.270	0.116	0.044	2.640	0.335	0.062	5.410
β_{23}	0.450	0.109	4.120	0.073	0.079	0.920	0.333	0.097	3.420
β_{31}	-0.249	0.061	4.050	-0.260	0.043	6.030	-0.251	0.063	3.970
β_{32}	-0.442	0.074	6.000	-0.435	0.050	8.640	-0.532	0.075	7.100
β_{33}	-0.652	0.124	5.250	-0.541	0.078	6.890	-1.014	0.154	6.580
β_{41}	-0.410	0.075	5.460	-0.042	0.055	0.770	-0.345	0.090	3.830
β_{42}	-0.156	0.086	1.810	0.020	0.073	0.270	-0.241	0.095	2.530
β_{43}	0.017	0.167	0.100	0.222	0.231	0.960	0.143	0.195	0.730
β_5	0.161	0.054	2.990	0.208	0.040	5.210	0.051	0.043	1.200
N		23			29			20	
R^2		0.579			0.545			0.679	
H_0^F		(4.380, 0.000)			(3.330, 0.000)			(1.660, 0.036)	
H_0^3		(14.070, 0.000)			(14.710, 0.000)			(10.550, 0.000)	

Table 10: Hypothesis Test Results Across Treatments

	Treatment A		Treatment B		Treatment C	
	$\|z\|$	$Prob. > \|z\|$	$\|z\|$	$Prob. > \|z\|$	$\|z\|$	$Prob. > \|z\|$
H_0^4	29.960	0.000	29.043	0.000	27.574	0.000
H_0^5	2.352	0.019	0.904	0.366	1.128	0.259
H_0^6	5.194	0.000	8.222	0.000	4.473	0.000
H_0^7	2.420	0.016	7.527	0.000	2.614	0.009

Table 11: Summary of Individual Hypothesis Test Results

Treatment		$<$	$=$	$>$
	H_0^5	8/23	0/23	2/23
A	H_0^5	11/23	1/23	1/23
	H_0^7	7/23	1/23	1/23
	H_0^5	8/29	4/29	4/29
B	H_0^6	9/29	3/29	3/29
	H_0^7	7/29	3/29	3/29
	H_0^5	6/20	3/20	2/20
C	H_0^6	10/20	1/20	1/20
	H_0^7	6/20	3/20	1/20

Table 12: Hansen (2000) Estimation Results

Backward Looking Model

	1975QI-2002QIV			1975QI-1982QIV			1983QI-2002QIV		
	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$
α_0	-8.418	5.037	1.671	2.329	7.843	0.297	-4.737	4.264	1.111
α_1	0.108	0.060	1.789	0.066	0.087	0.761	0.069	0.051	1.344
α_2	0.507	0.119	4.258	0.037	0.157	0.235	0.559	0.120	4.650
α_3	0.378	0.113	3.356	0.084	0.148	0.564	0.077	0.097	0.792
α_4	0.021	0.020	1.029	0.034	0.036	0.953	-0.010	0.013	0.760
Obs.		112			32			80	
R^2		0.819			0.034			0.491	
Break Est.:	1982QIV								
95% C. I.:	1982QII-1983QI								

Mixture Model

	1975QI-2002QIV			1975QI-1983QIV			1984QI-2002QIV		
	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$
α_0	-13.185	3.303	3.992	-16.772	4.128	4.063	-7.234	4.591	1.576
α_1	0.159	0.039	4.032	0.223	0.056	3.974	0.095	0.056	1.680
α_2	0.058	0.125	0.466	-0.181	0.167	1.084	0.380	0.151	2.521
α_3	-0.012	0.117	0.103	-0.111	0.131	0.844	-0.046	0.117	0.397
α_4	0.899	0.133	6.773	1.069	0.199	5.359	0.391	0.126	3.110
α_5	0.030	0.016	1.887	0.069	0.027	2.610	-0.006	0.013	0.464
Obs.		112			36			76	
R^2		0.877			0.616			0.589	
Break Est.:	1983QIV								
95% C. I.:	1982QII-1991QII								

Table 13: Bai and Perron (1998) Estimation Results

	Backward Looking Model			Mixture Model		
		Value	5% Crit.		Value	5% Crit.
$\sup F(0\|k)$ Tests	$0\|1$	27.389	18.230	$0\|1$	27.594	20.080
	$0\|2$	28.945	15.620	$0\|2$	25.730	17.370
	$0\|3$	34.047	13.930	$0\|3$	30.552	15.580
	$0\|4$	32.312	12.380	$0\|4$	41.677	13.900
	$0\|5$	27.737	10.520	$0\|5$	32.983	11.940
$D\max$ Tests	$UD\max$	34.047	18.420	$UD\max$	41.677	20.300
	$WD\max$	48.065	19.960	$WD\max$	60.206	21.860
$\sup F(k+1\|k)$ Tests	$2\|1$	54.603	18.230	$2\|1$	43.140	20.080
	$3\|2$	39.823	19.910	$3\|2$	35.001	22.110
	$4\|3$	15.247	20.990	$4\|3$	35.616	23.040
	$5\|4$	6.404	21.710	$5\|4$	4.890	23.770
Sequential Breaks						
	Est.	95% C. I.		Est.	95% C. I.	
1^{st} Break	1982QIV	1982QII	1983QII	1983QIV	1982QIV	1984QII
2^{nd} Break	1991QI	1990QIII	1991QIII	1997QI	1996QI	1997QII
3^{rd} Break	..	..	..	1991QI	1990QIII	1991QIV

Table 14: Kim and Nelson (1999) Estimation Results

Backward Looking Model				Mixture Model			
Std. Dev. of	Est.	Std. Err.	$\|t\|$	Std. Dev. of	Est.	Std. Err.	$\|t\|$
α_0	0.000	0.616	0.000	α_0	0.000	0.250	4.687
α_1	0.010	0.001	0.001	α_1	0.000	0.003	0.000
α_2	0.232	0.035	6.900	α_2	0.083	0.040	0.000
α_3	0.000	0.028	6.631	α_3	0.000	0.019	2.067
α_4	0.006	0.004	0.000	α_4	0.177	0.037	0.000
σ	0.000	0.365	1.587	α_5	0.005	0.004	4.747
				σ	0.521	0.111	1.223
$\log L$	-179.680			$\log L$	-159.680		
R^2	0.666	LM	26.012	R^2	0.767	LM	9.322

Table 15: Maximum Likelihood Estimates I

	1962QII-2003QI			1962QII-1984QII			1984QIII-2003QI		
	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$
ω	0.013	0.008	1.759	0.014	0.009	1.606	0.035	0.011	3.238
α_x	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
α_π	0.000	0.000	0.000	0.000	0.000	0.000	0.085	0.070	1.206
ρ_r	1.032	0.037	28.241	1.020	0.031	32.667	0.939	0.017	55.817
ρ_π	0.000	0.002	0.000	0.000	0.003	0.000	0.051	0.042	1.213
ρ_g	0.288	0.120	2.406	0.307	0.158	1.943	0.000	0.000	0.000
ρ_u	14.151	11.736	1.206	13.961	12.200	1.144	5.059	1.073	4.715
ρ_a	0.970	0.017	55.571	0.975	0.018	54.212	0.979	0.003	378.050
ρ_e	0.974	0.016	60.672	0.956	0.030	31.390	0.080	0.105	0.763
σ_a	0.108	0.059	1.843	0.132	0.089	1.488	0.060	0.009	6.786
σ_e	0.006	0.003	2.163	0.009	0.005	1.608	0.003	0.001	2.485
σ_z	0.009	0.000	17.679	0.010	0.001	12.976	0.007	0.001	11.703
σ_r	0.008	0.003	2.721	0.009	0.004	2.319	0.007	0.001	11.927
$\log L$		-1907.200			-1010.100			-902.970	

Table 16: Maximum Likelihood Estimates II

	1962QII-2003QI			1962QII-1984QII			1984QIII-2003QI		
	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$
ω	0.012	0.008	1.511	0.017	0.015	1.168	0.000	0.000	0.000
ψ	6.752	4.515	1.496	8.229	5.516	1.492	0.002	0.001	1.778
α_x	0.000	0.000	0.000	0.000	0.000	0.000	0.725	0.146	4.961
α_π	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.097	0.030
ρ_r	1.028	0.025	41.380	1.025	0.041	24.850	0.980	0.024	40.409
ρ_π	0.000	0.000	0.000	0.000	0.003	0.000	0.102	0.046	2.228
ρ_g	0.289	0.089	3.224	0.308	0.176	1.754	0.231	0.072	3.188
ρ_u	12.282	11.114	1.105	17.305	15.058	1.149	0.000	0.000	0.001
ρ_a	0.971	0.004	260.130	0.972	0.017	56.679	0.979	0.016	62.041
ρ_e	0.974	0.011	90.531	0.956	0.021	44.885	0.000	0.000	0.000
σ_a	0.114	0.013	8.775	0.121	0.067	1.803	0.096	0.068	1.400
σ_e	0.000	0.000	3.954	0.000	0.000	2.476	0.005	0.001	7.829
σ_z	0.009	0.001	16.608	0.010	0.001	13.002	0.004	0.001	3.048
σ_r	0.008	0.003	2.841	0.010	0.004	2.609	0.002	0.000	7.267
$\log L$		-1907.200			-1010.100			-929.760	

Table 17: Maximum Likelihood Estimates III

	1962QII-2003QI			1962QII-1984QII			1984QIII-2003QI		
	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$	Est.	Std. Err.	$\|t\|$
ω	0.017	0.018	0.958	0.015	0.018	0.844	0.035	0.026	1.365
θ	8.534	7.142	1.195	3.480	2.786	1.249	9.450	6.805	1.389
ϕ	71.880	30.144	2.385	47.016	8.571	5.485	41.139	12.534	3.282
α_x	0.000	0.002	0.002	0.000	0.000	0.001	0.000	0.000	0.000
α_π	0.000	0.010	0.037	0.197	0.079	2.493	0.000	0.000	0.001
ρ_π	0.000	0.001	0.440	0.353	0.843	0.419	0.000	0.000	0.180
ρ_g	0.256	0.079	3.237	0.511	0.442	1.157	0.264	0.099	2.655
ρ_u	9.355	3.413	2.741	11.430	4.568	2.502	9.370	7.663	1.223
ρ_a	0.952	0.034	27.673	0.968	0.029	33.595	0.940	0.034	27.813
ρ_θ	0.978	0.017	58.175	0.958	0.050	19.247	0.952	0.009	103.450
σ_a	0.065	0.046	1.395	0.068	0.059	1.141	0.057	0.029	1.972
σ_θ	0.005	0.000	1.349	0.005	0.005	0.462	0.007	0.000	5.352
σ_z	0.009	0.001	17.035	0.007	0.001	12.074	0.010	0.001	12.283
σ_r	0.007	0.001	5.569	0.015	0.007	2.095	0.008	0.002	3.179
$\log L$		-1848.400			-962.350			-896.580	
Mark-up		13.273%			40.326%			11.834%	

APPENDIX C

FIGURES

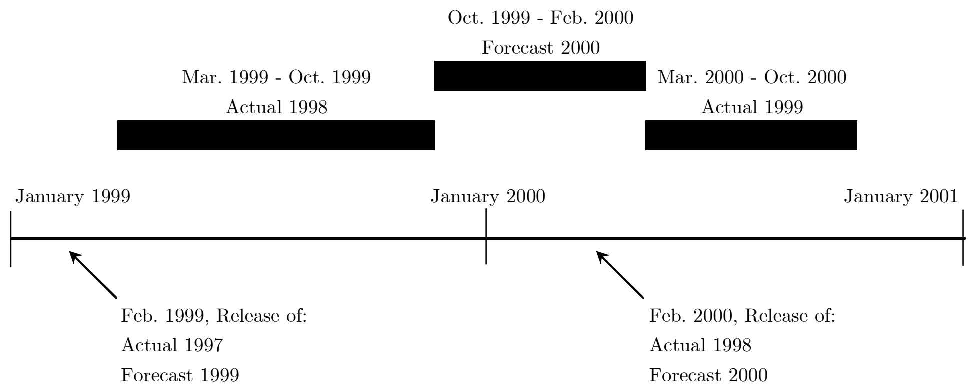

Figure 1: Survey Phases

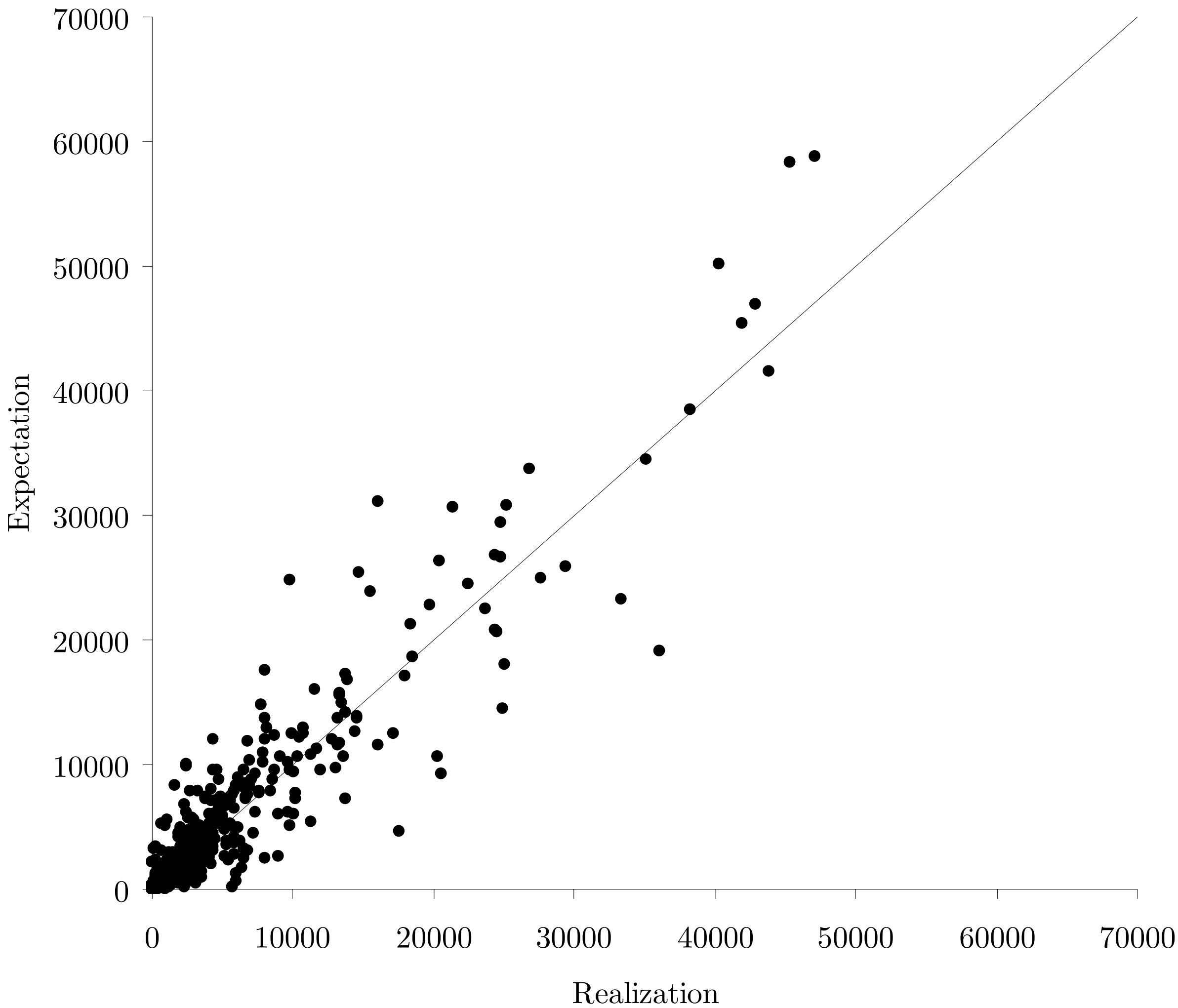

Figure 2: 1986(a), x_{it} vs. y_{it}

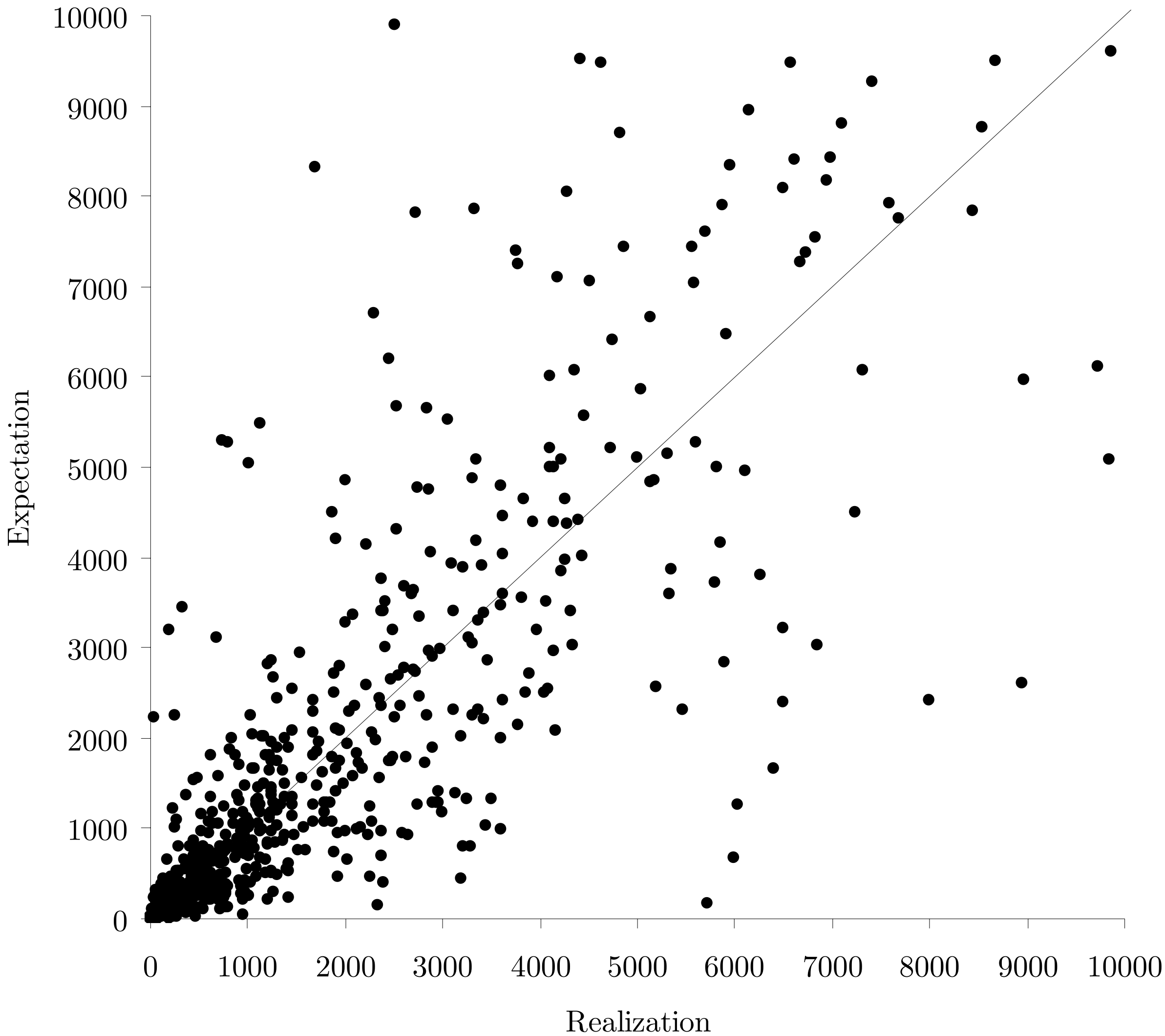

Figure 3: 1986(b), x_{it} vs. y_{it}

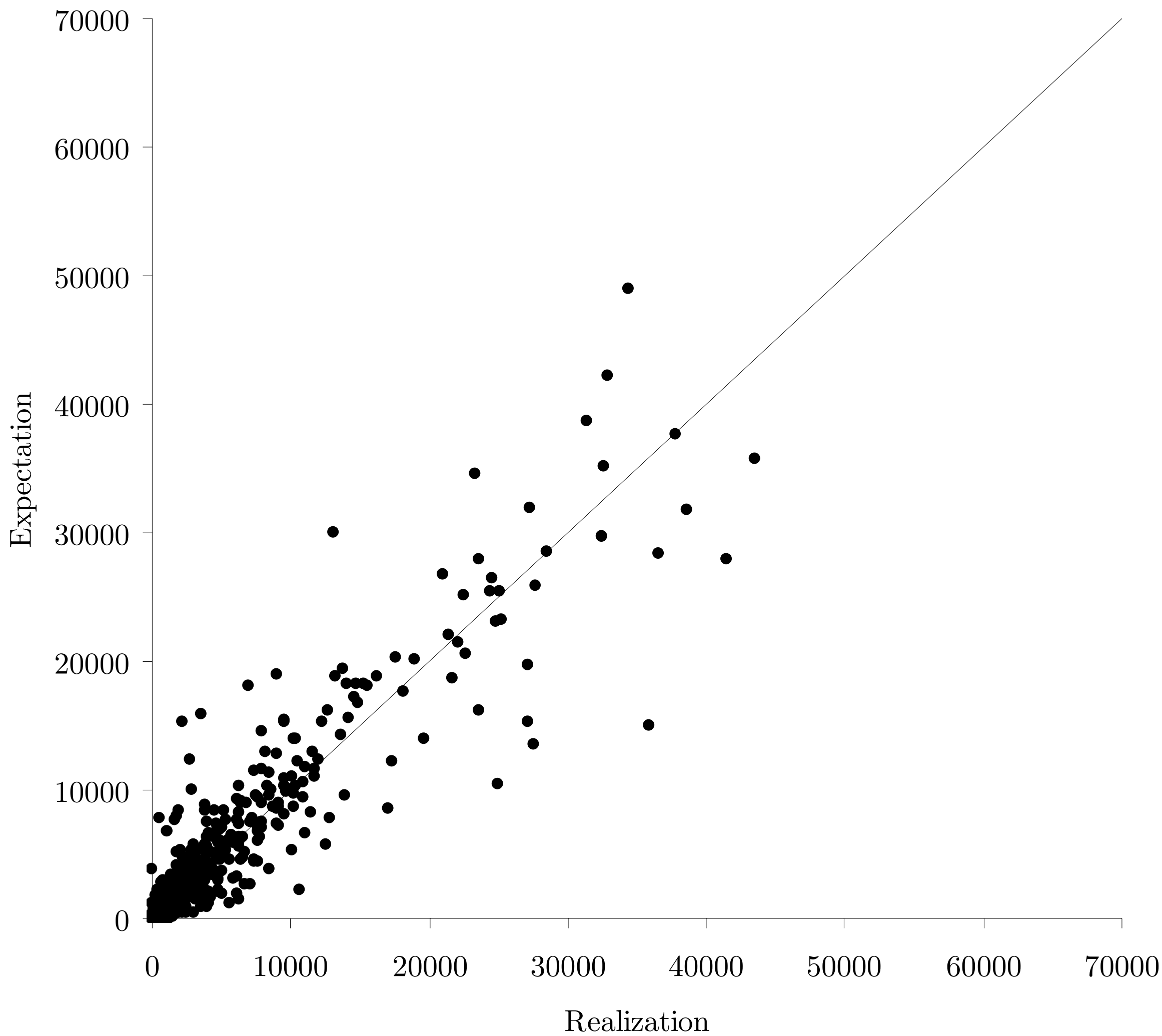

Figure 4: 1987(a), x_{it} vs. y_{it}

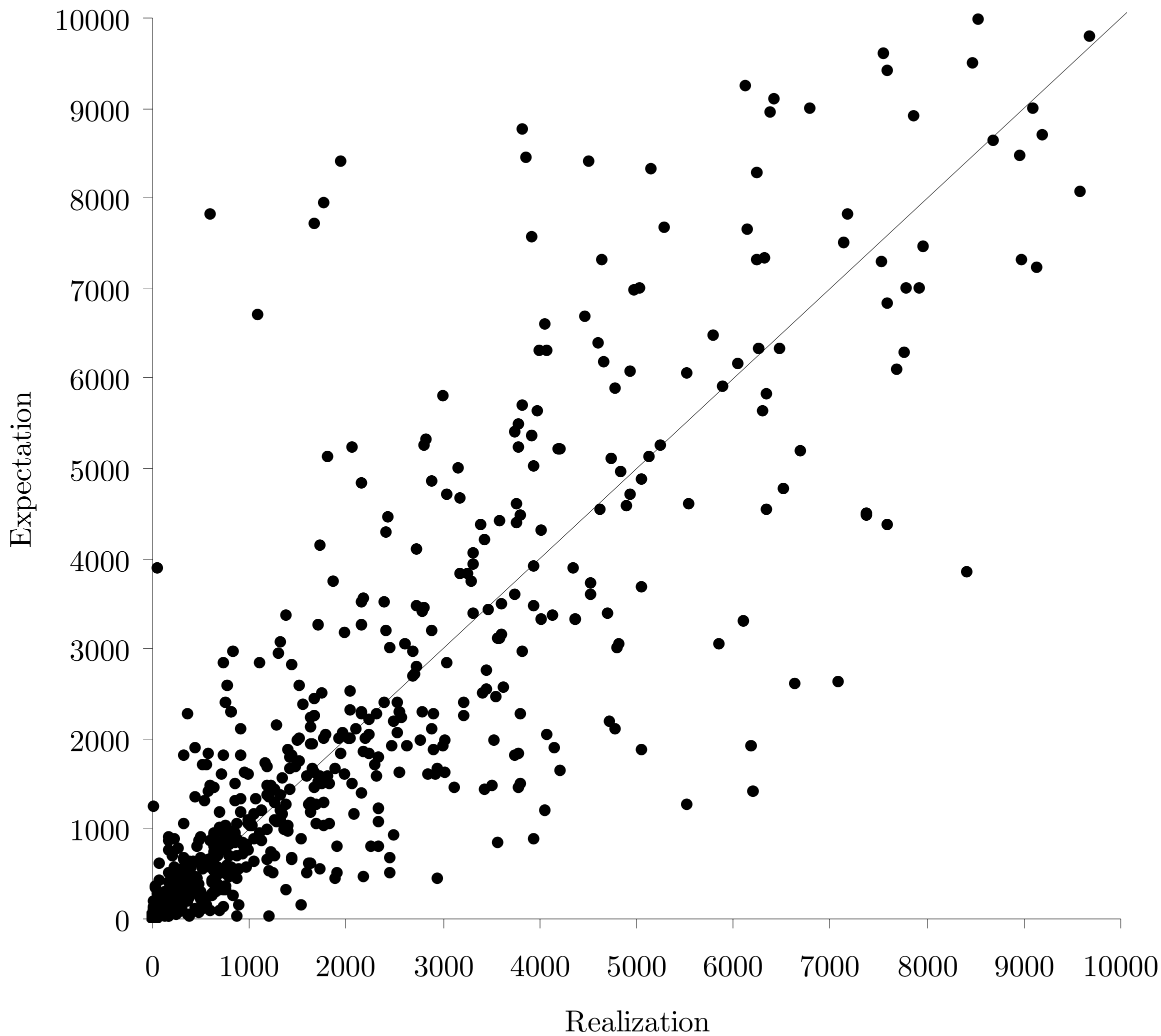

Figure 5: 1987(b), x_{it} vs. y_{it}

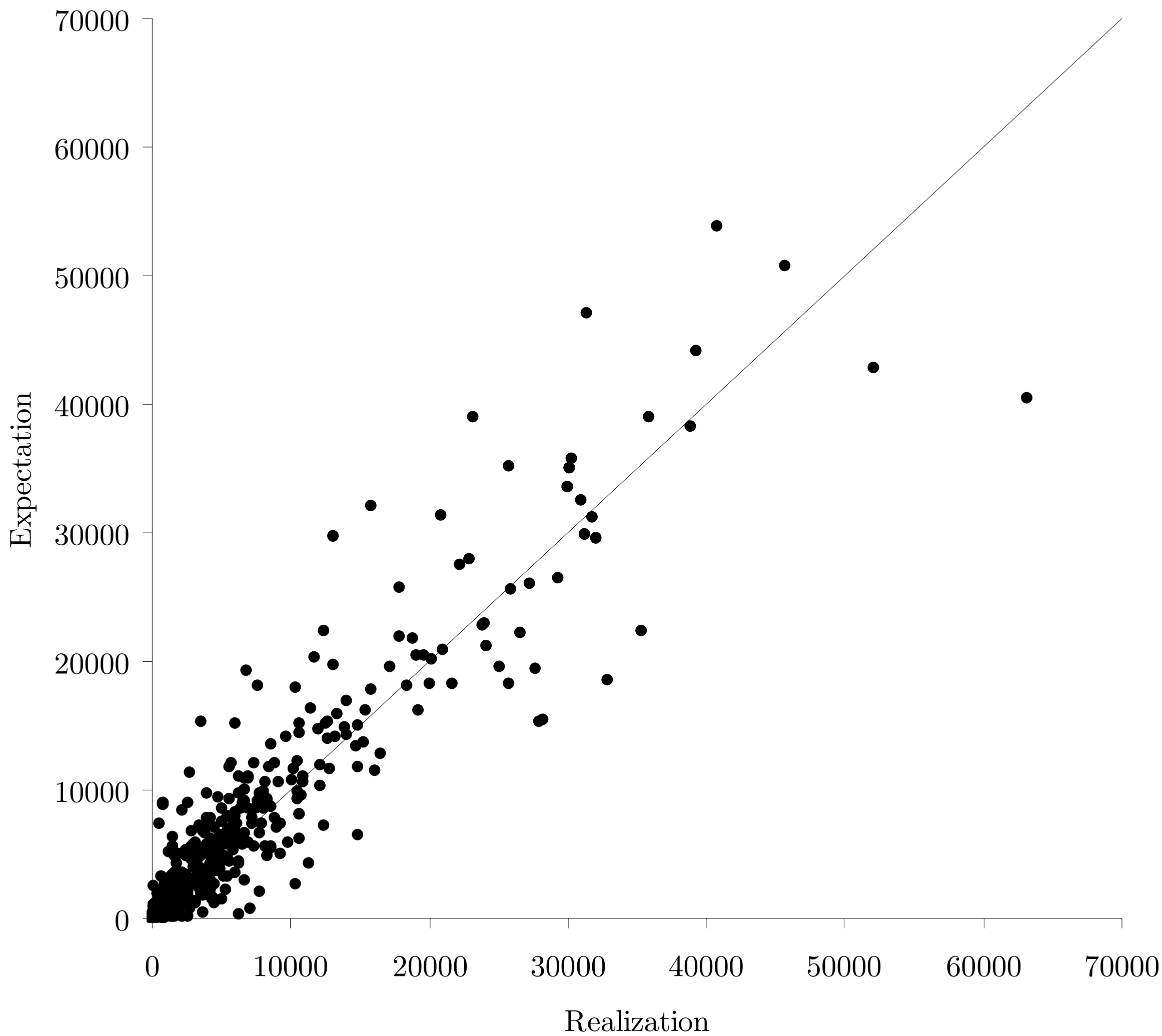

Figure 6: 1988(a), x_{it} vs. y_{it}

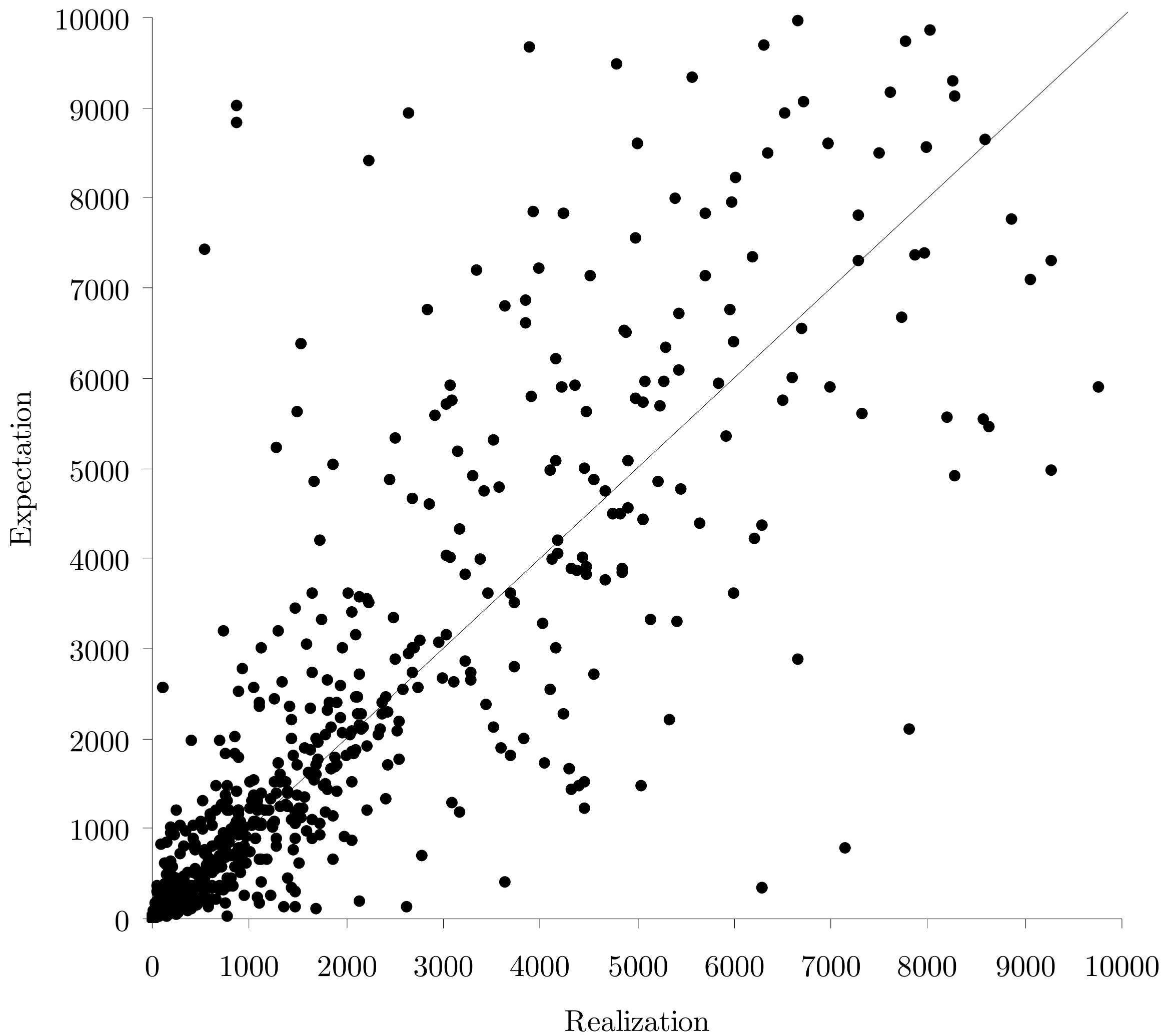

Figure 7: 1988(b), x_{it} vs. y_{it}

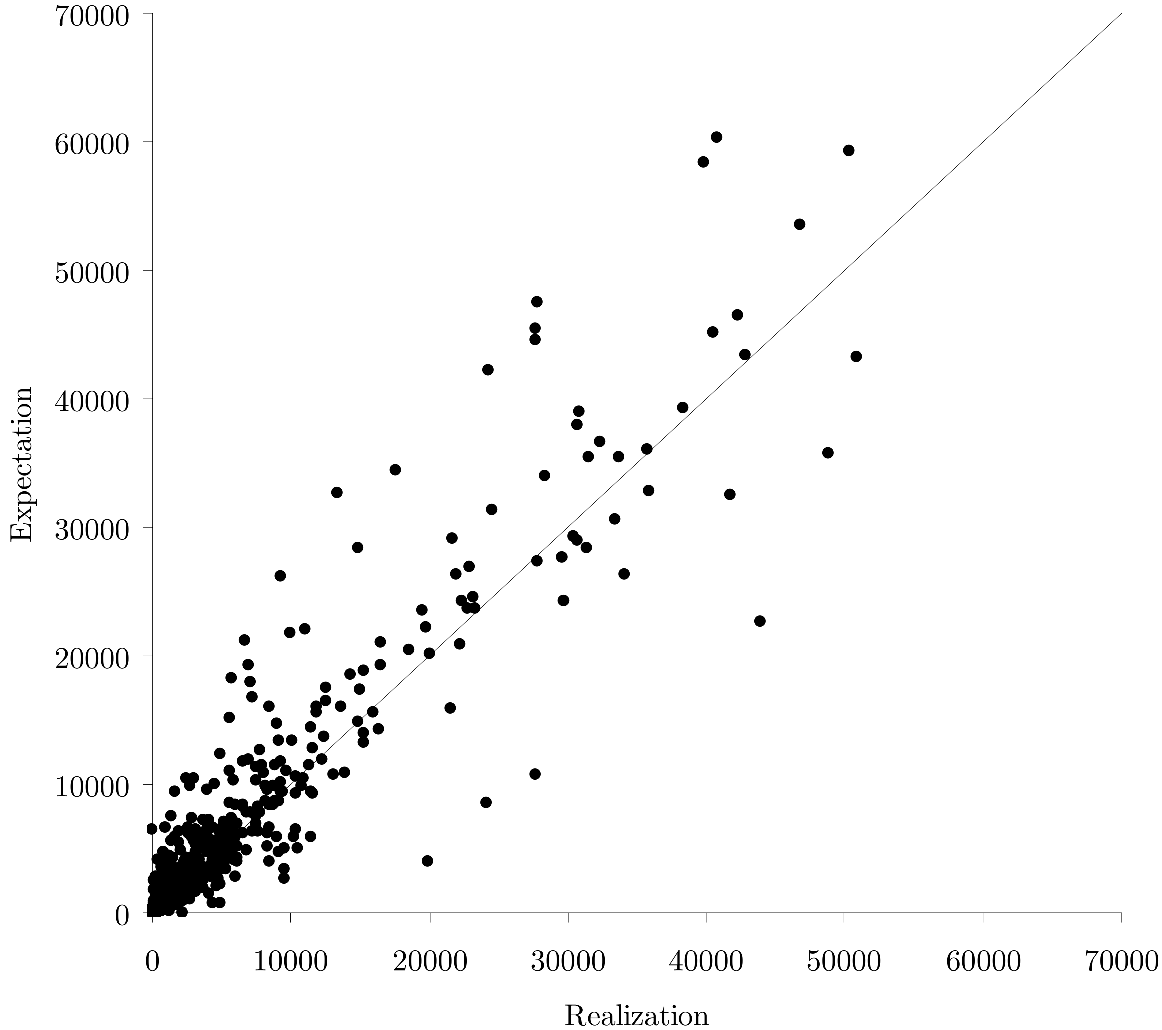

Figure 8: 1989(a), x_{it} vs. y_{it}

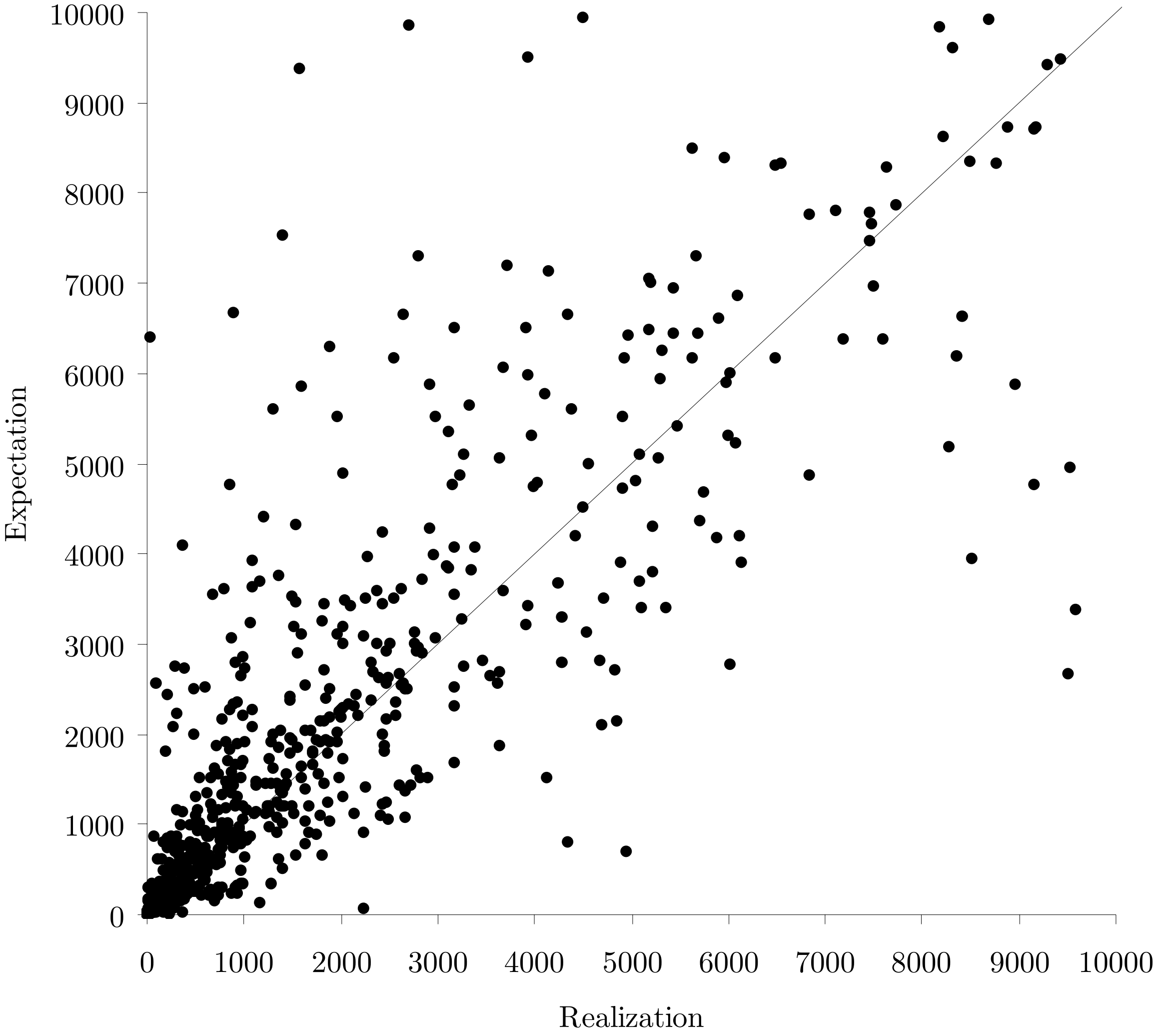

Figure 9: 1989(b), x_{it} vs. y_{it}

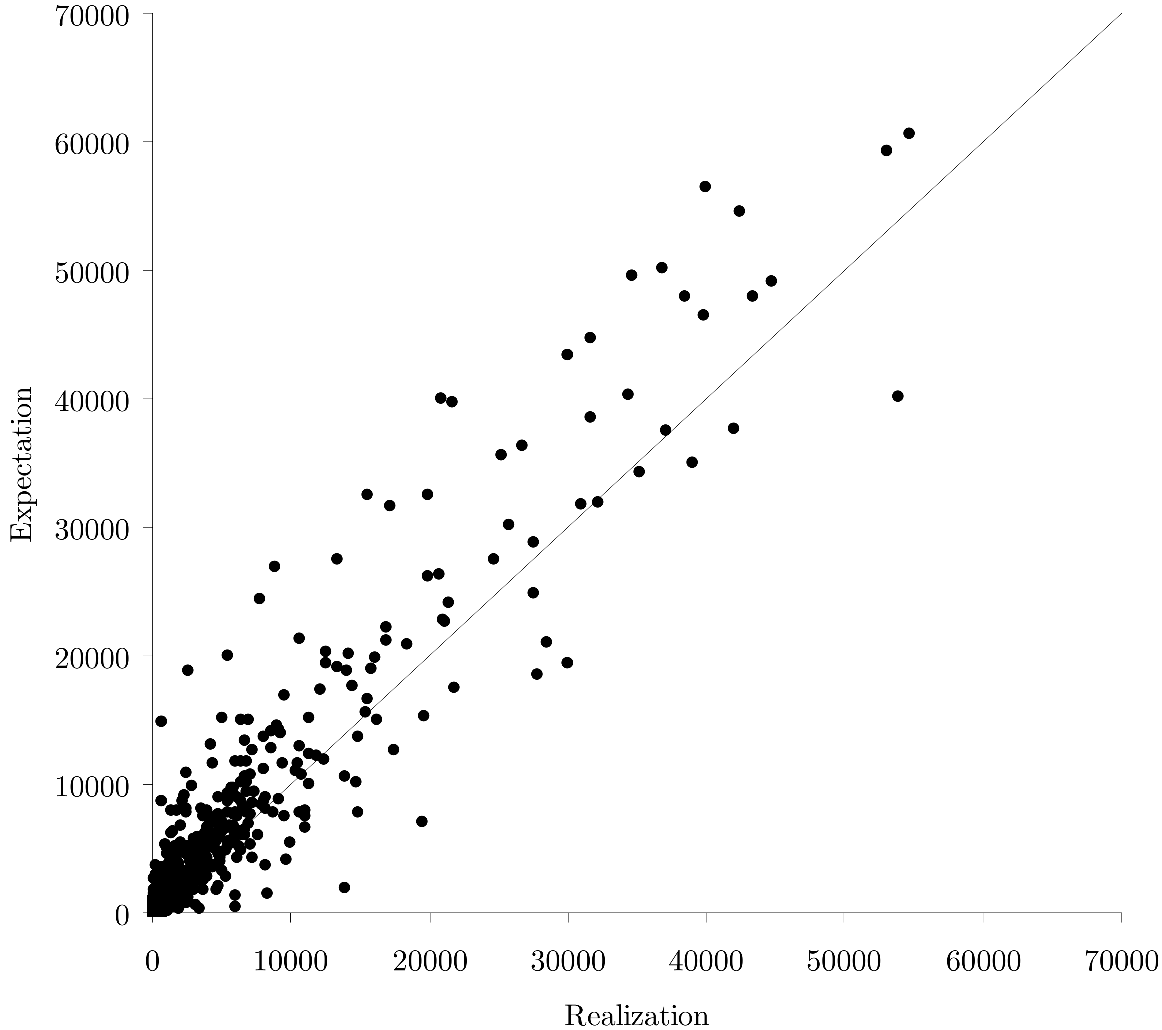

Figure 10: 1990(a), x_{it} vs. y_{it}

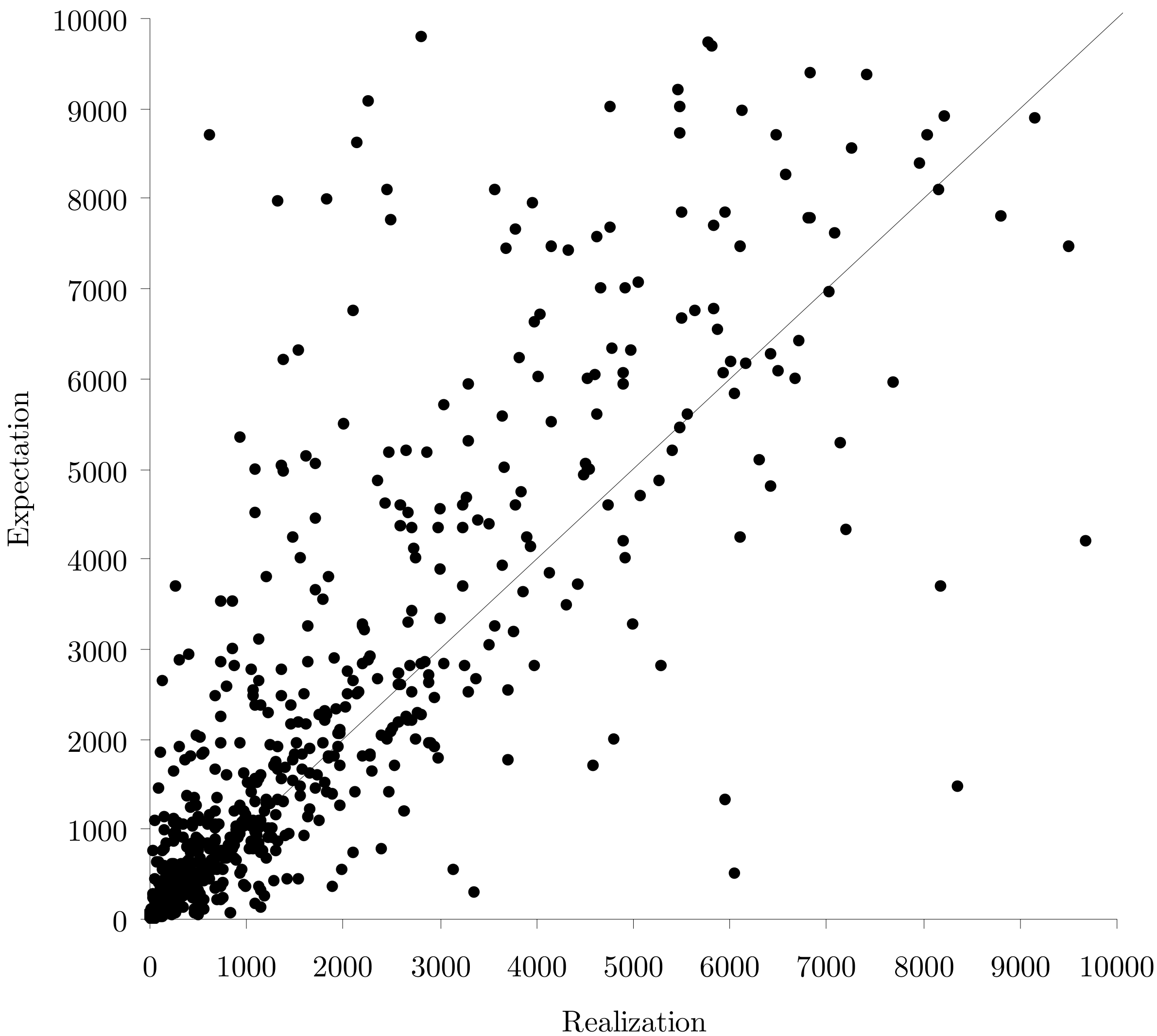

Figure 11: 1990(b), x_{it} vs. y_{it}

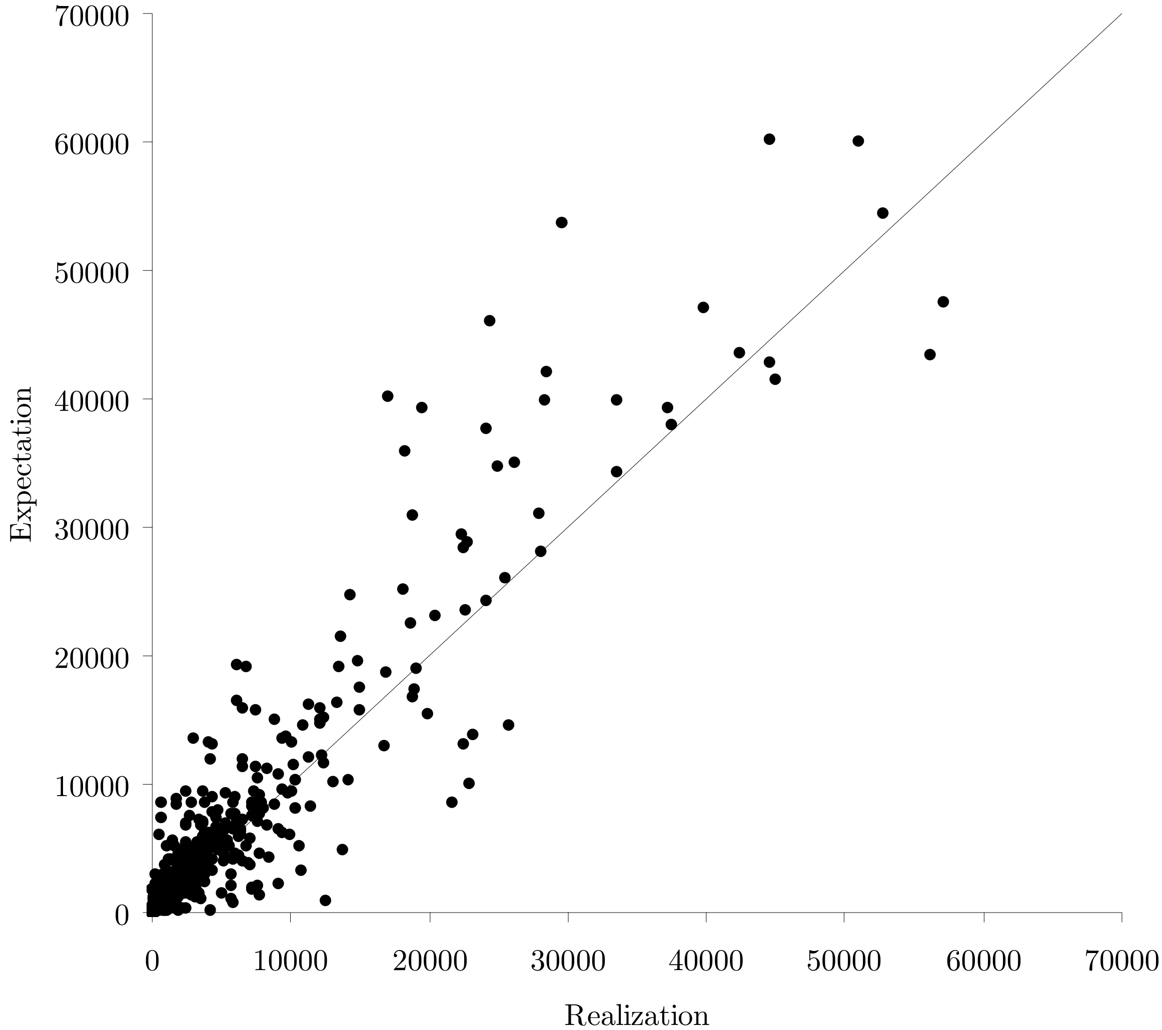

Figure 12: 1991(a), x_{it} vs. y_{it}

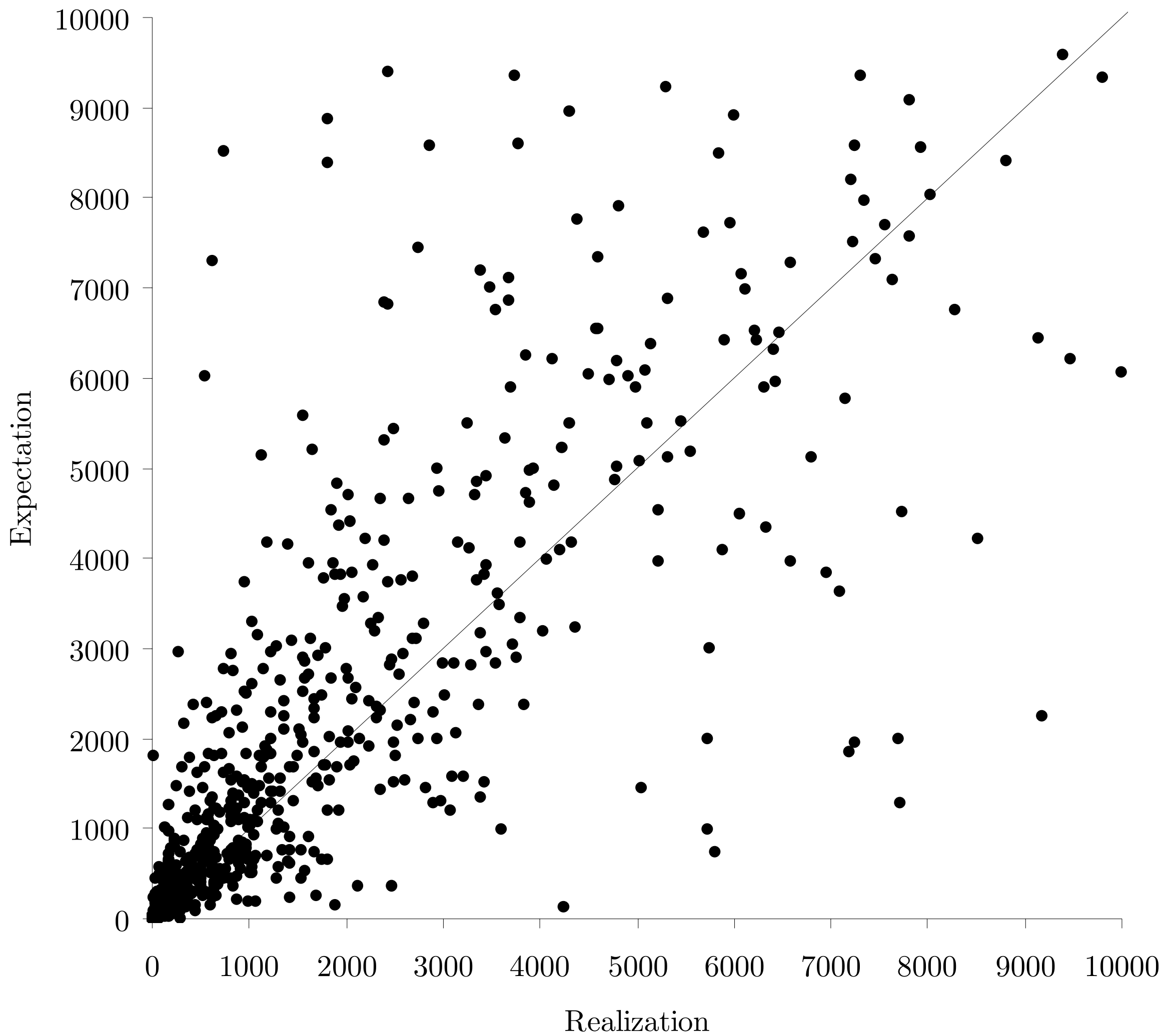

Figure 13: 1991(b), x_{it} vs. y_{it}

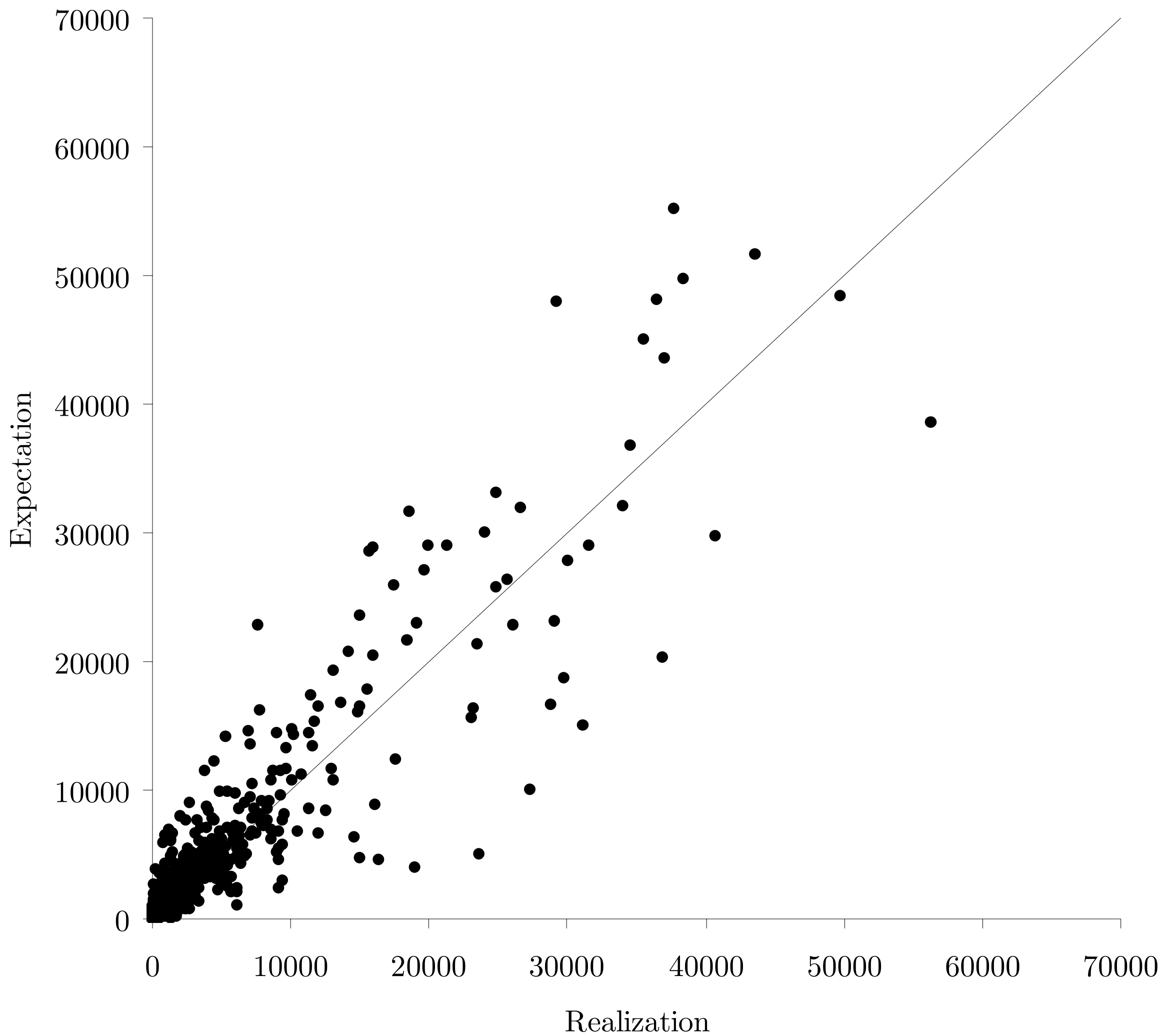

Figure 14: 1992(a), x_{it} vs. y_{it}

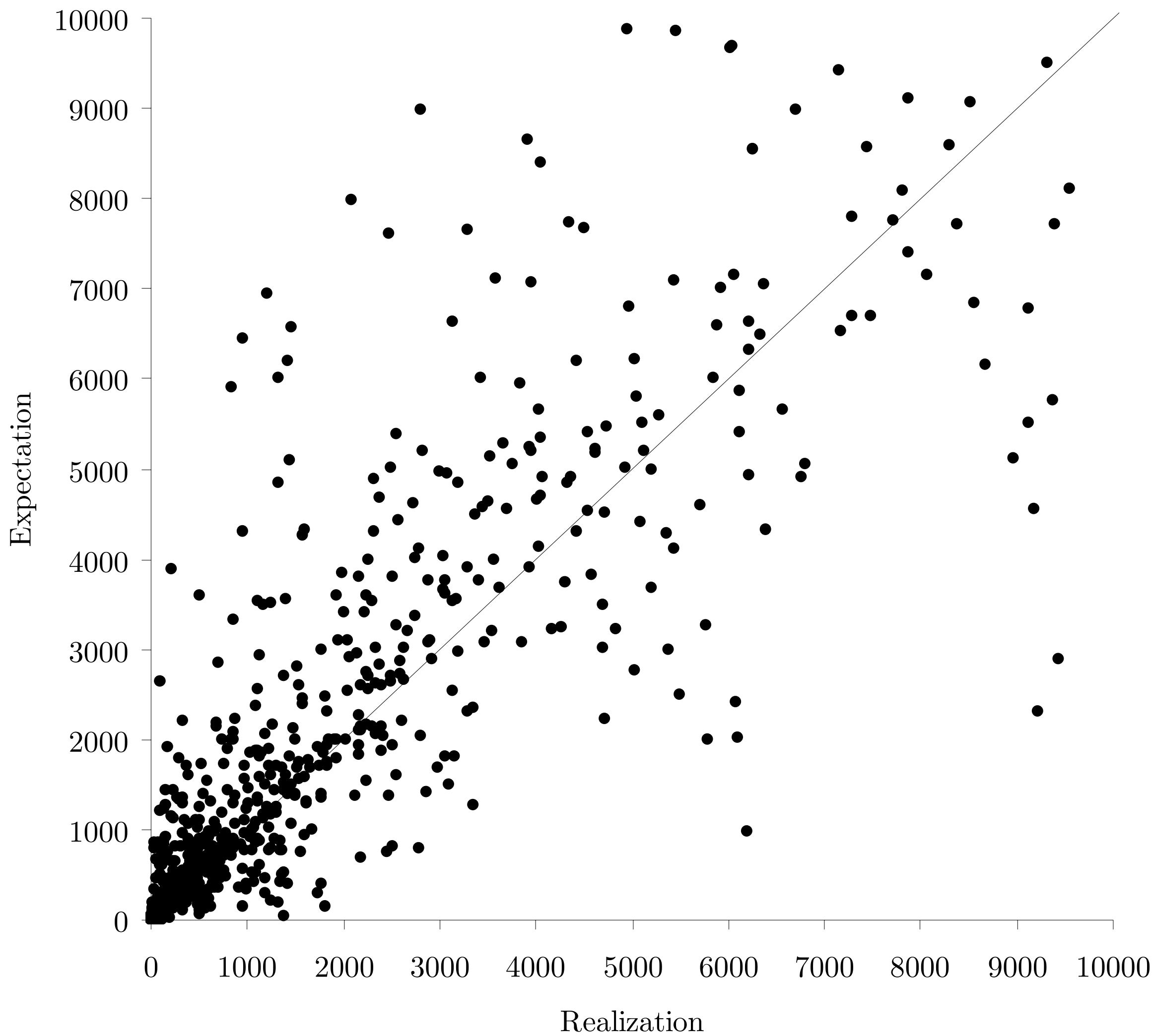

Figure 15: 1992(b), x_{it} vs. y_{it}

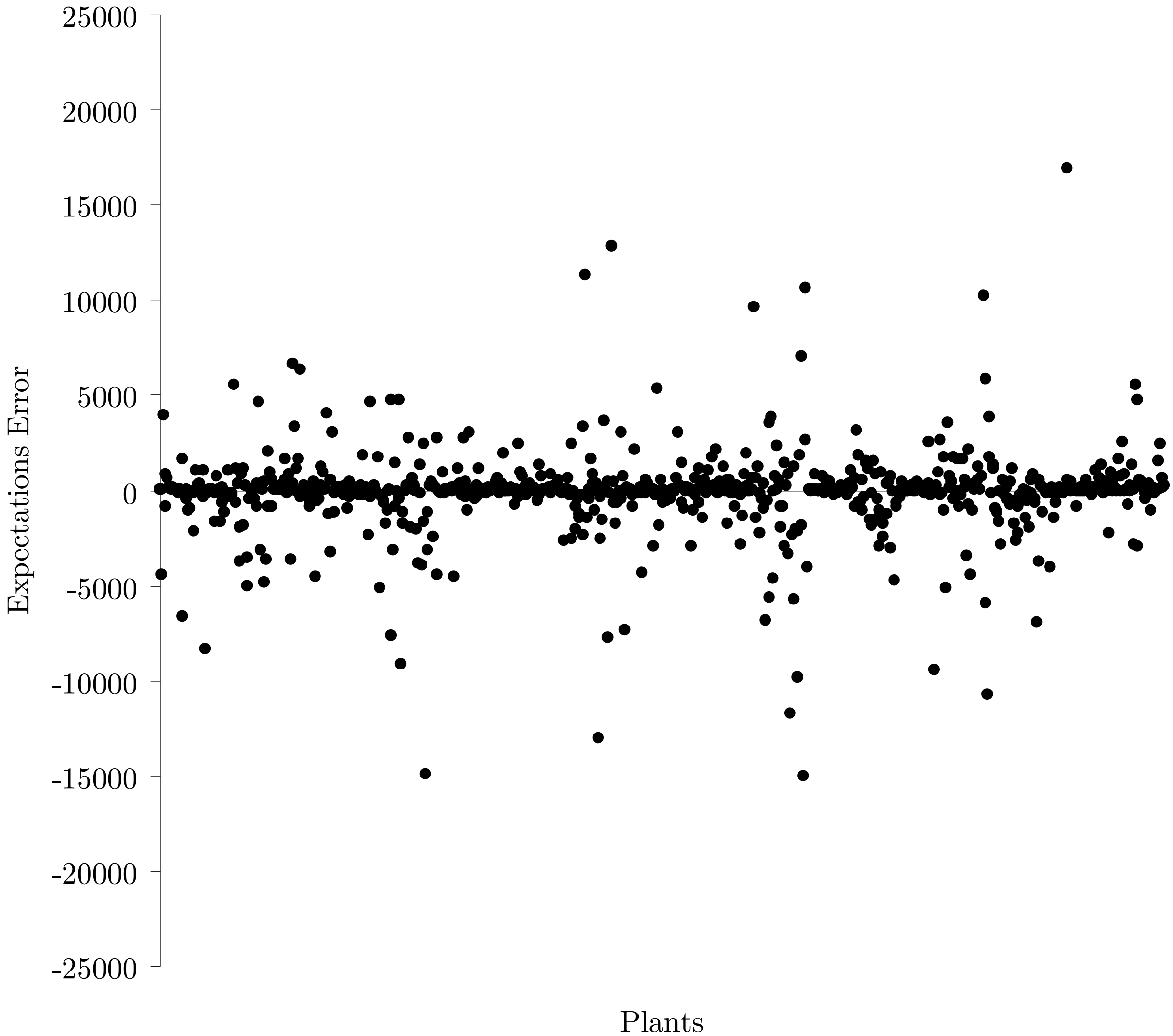

Figure 16: 1986(a), ε_{it} vs. i

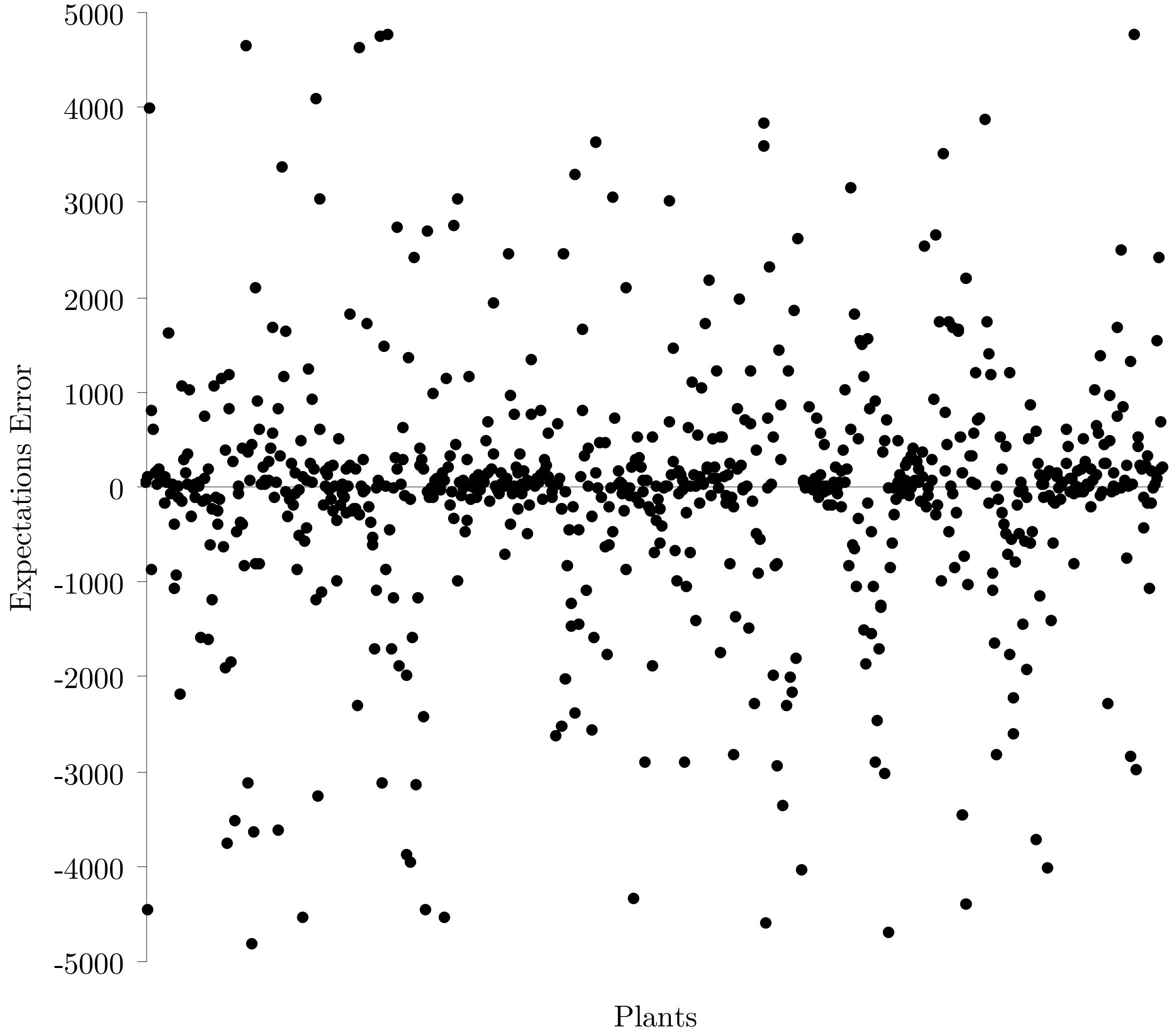

Figure 17: 1986(b), ε_{it} vs. i

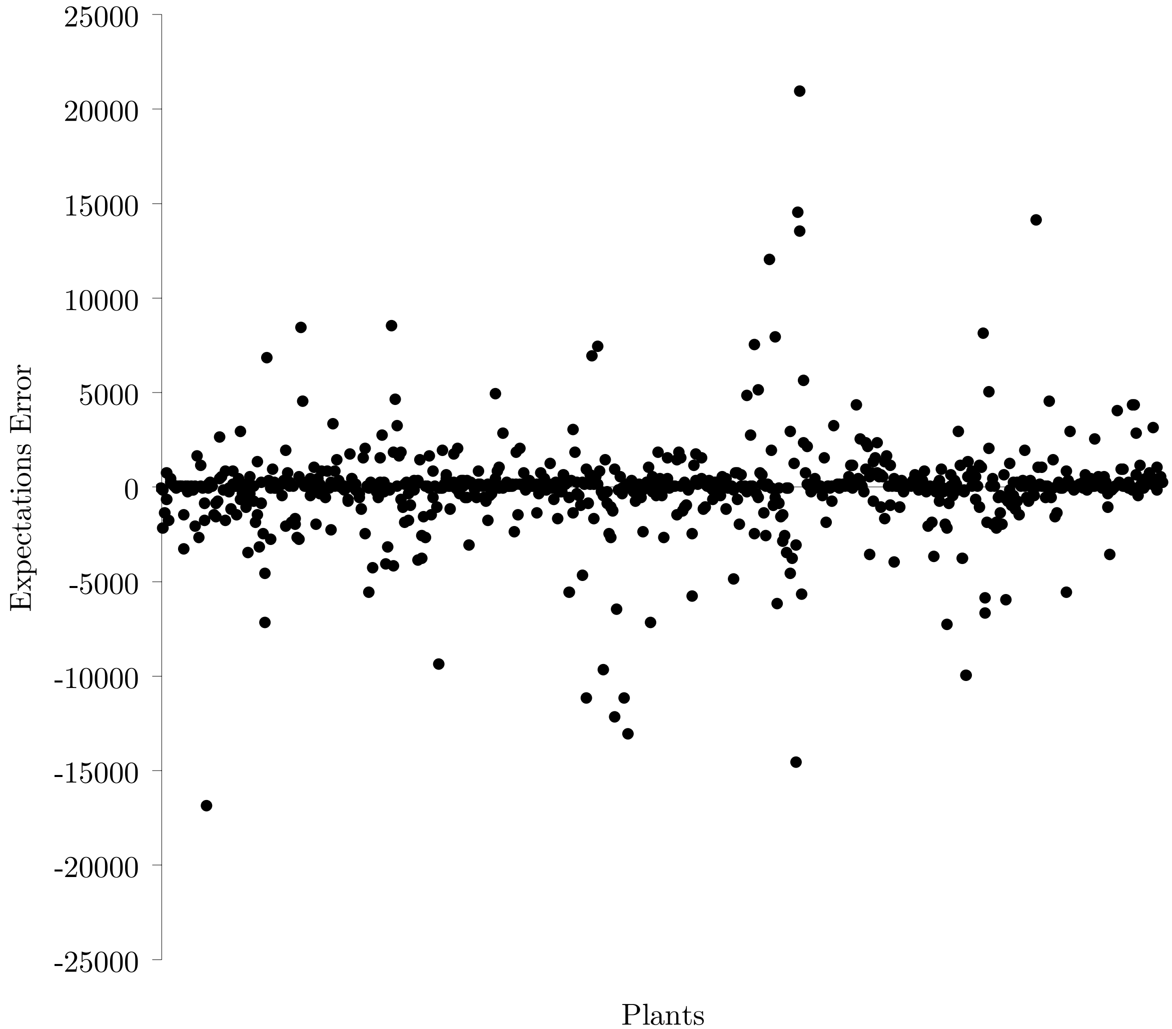

Figure 18: 1987(a), ε_{it} vs. i

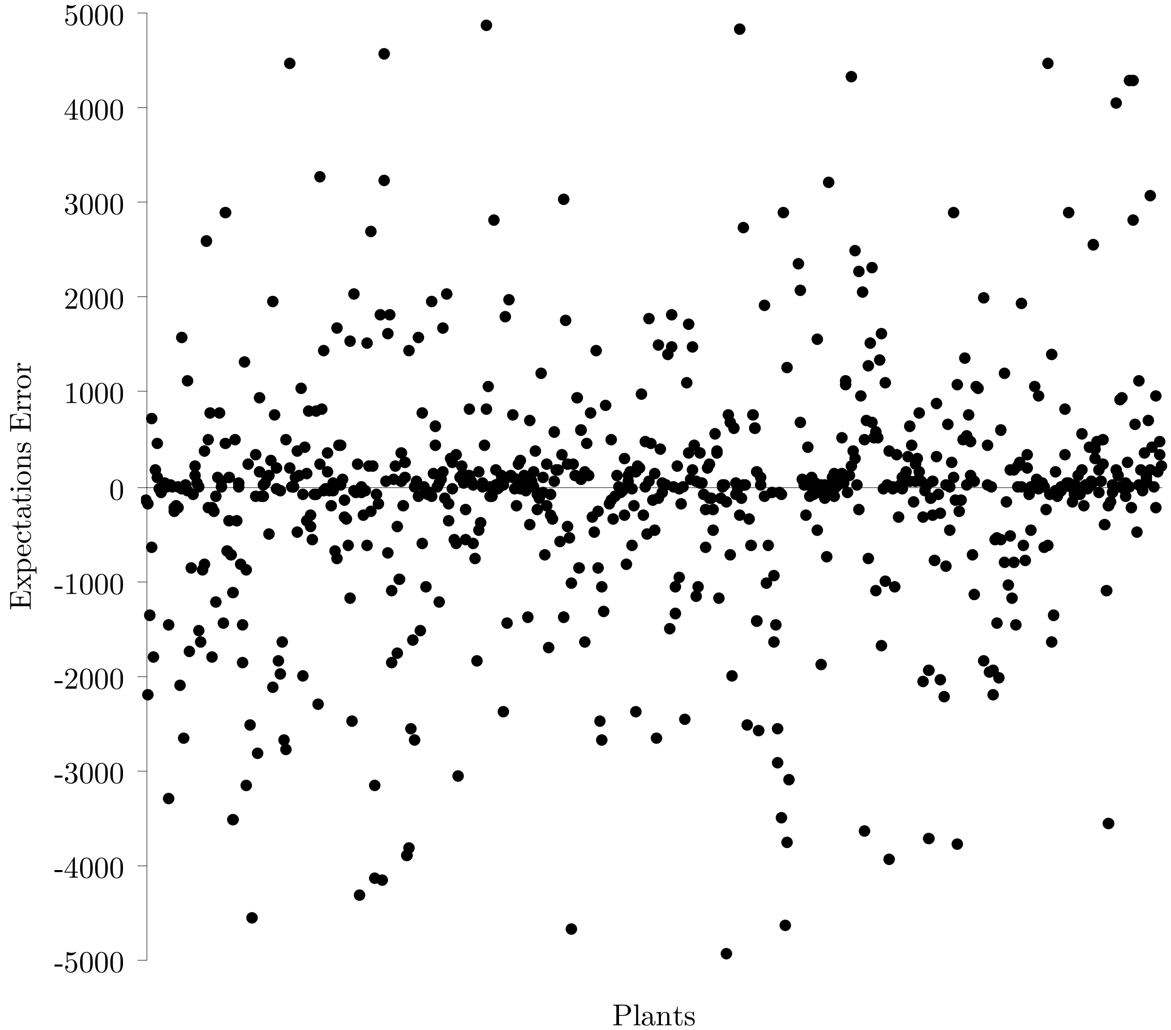

Figure 19: 1987(b), ε_{it} vs. i

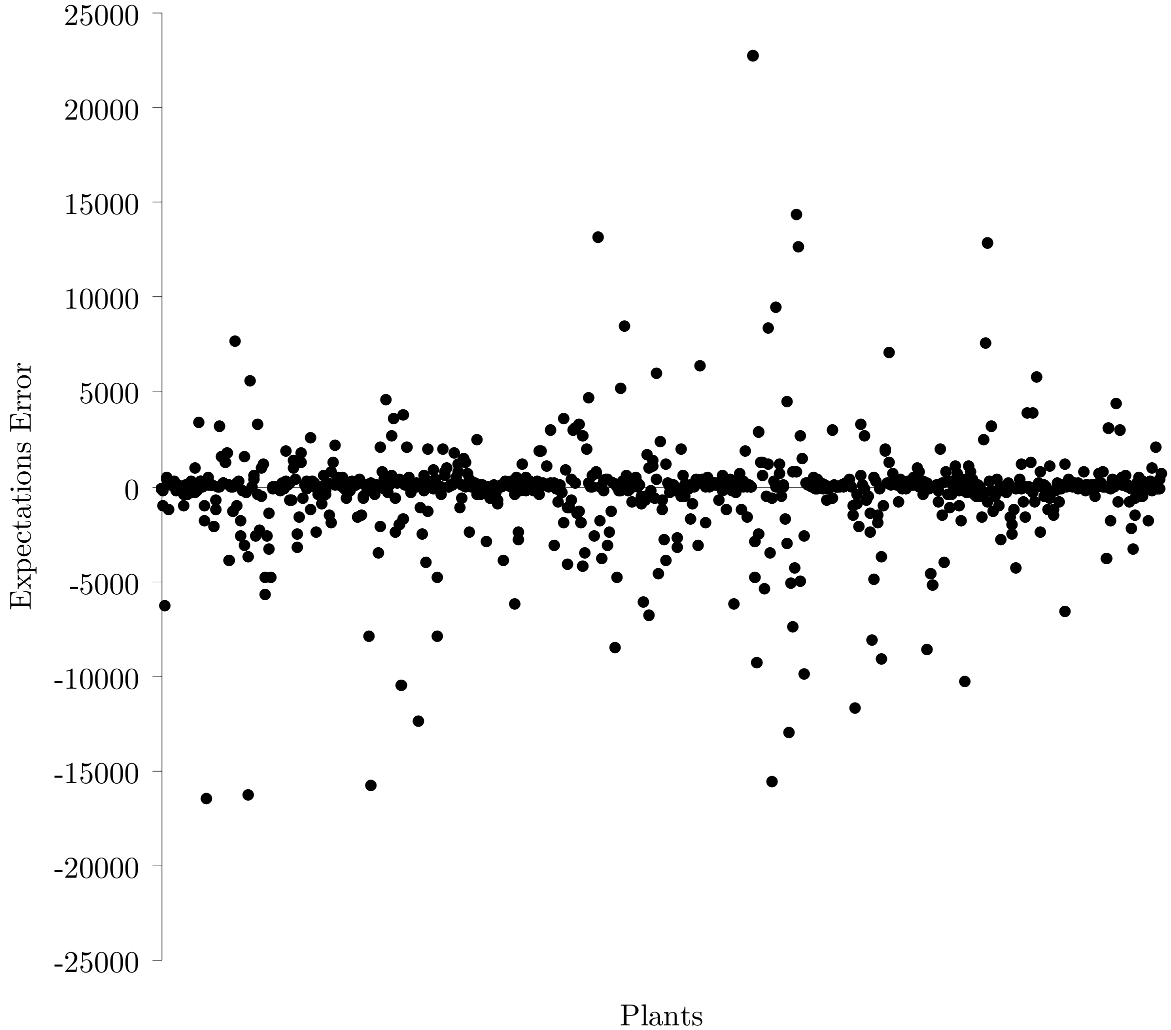

Figure 20: 1988(a), ε_{it} vs. i

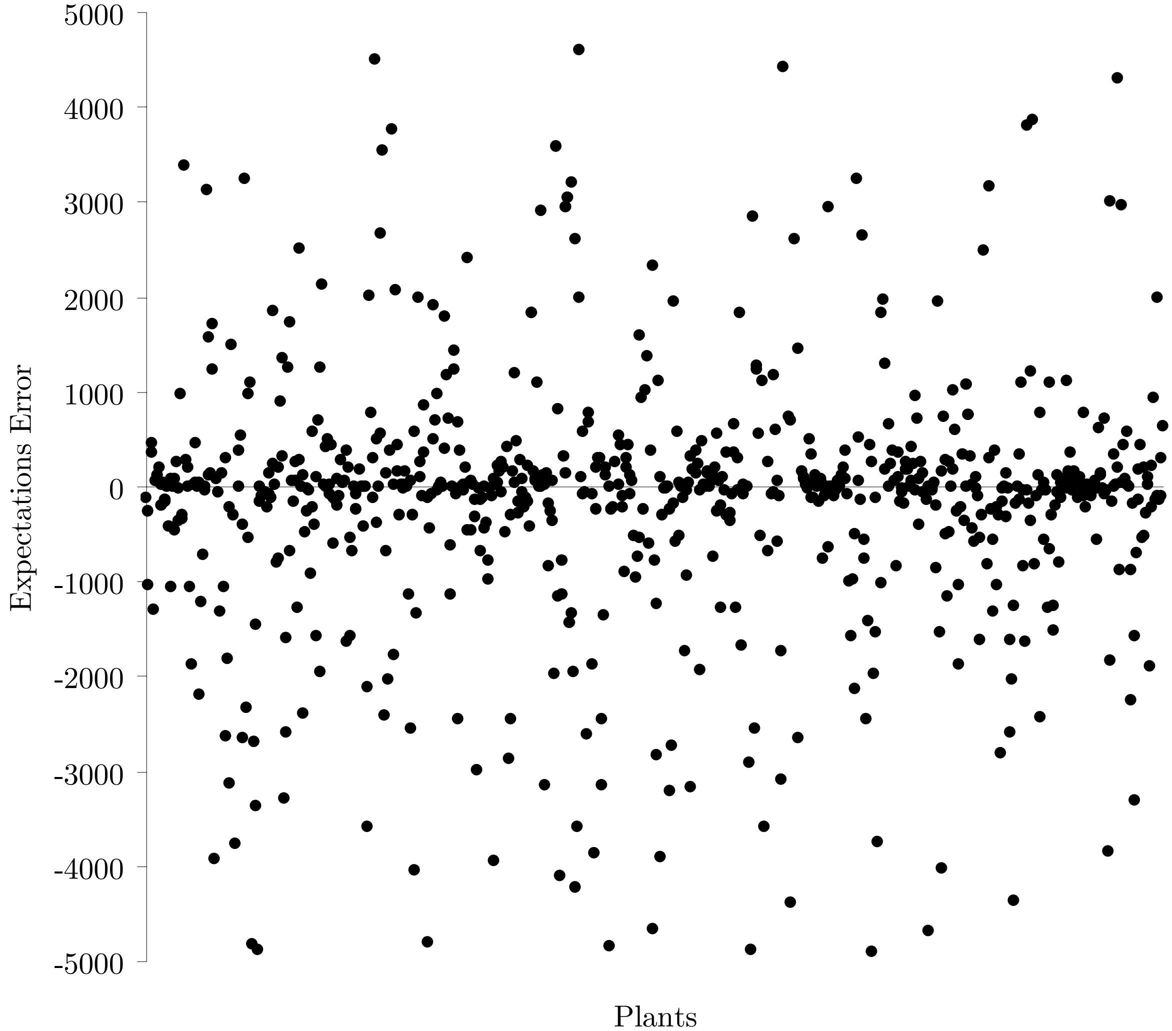

Figure 21: 1988(b), ε_{it} vs. i

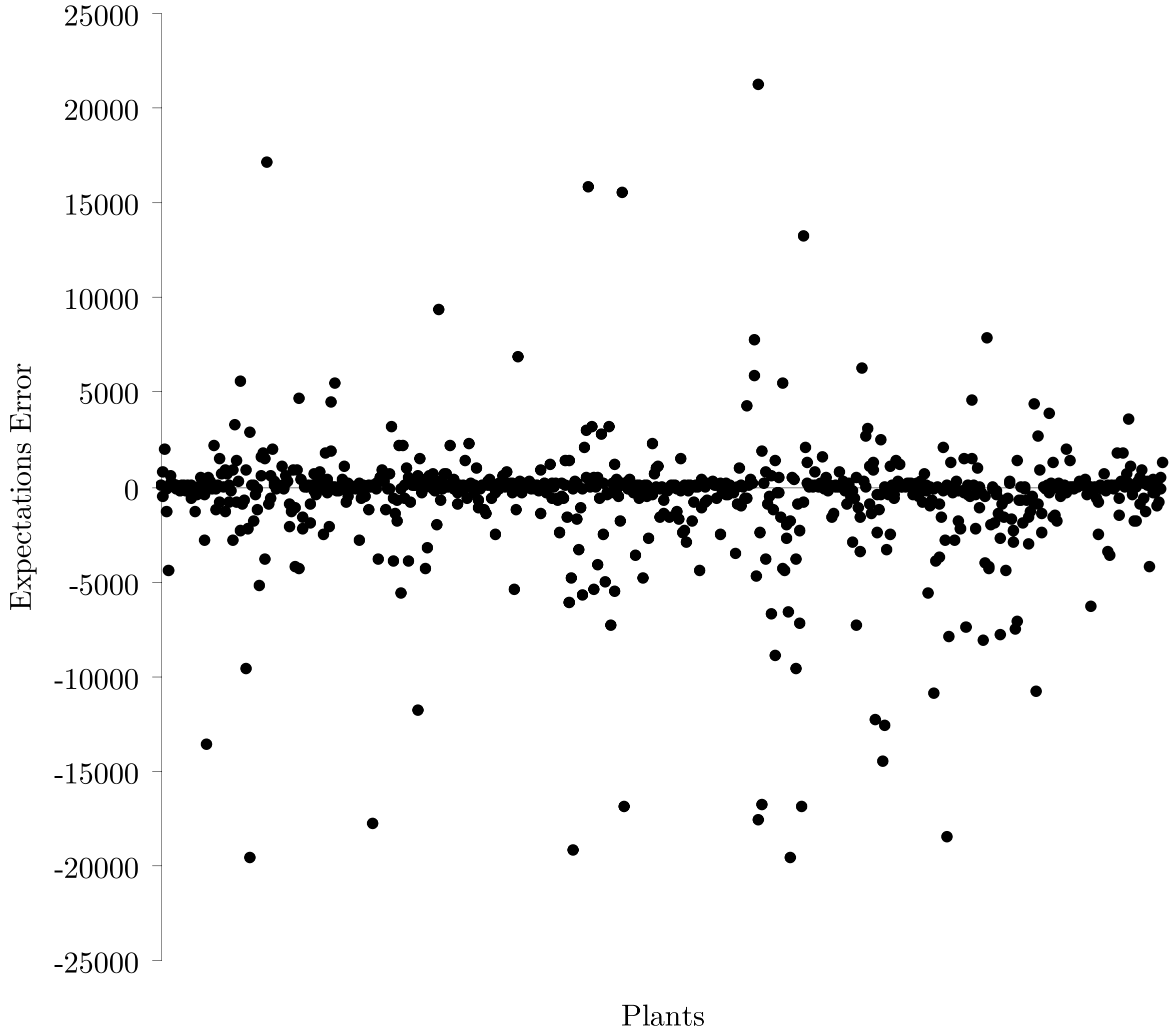

Figure 22: 1989(a), ε_{it} vs. i

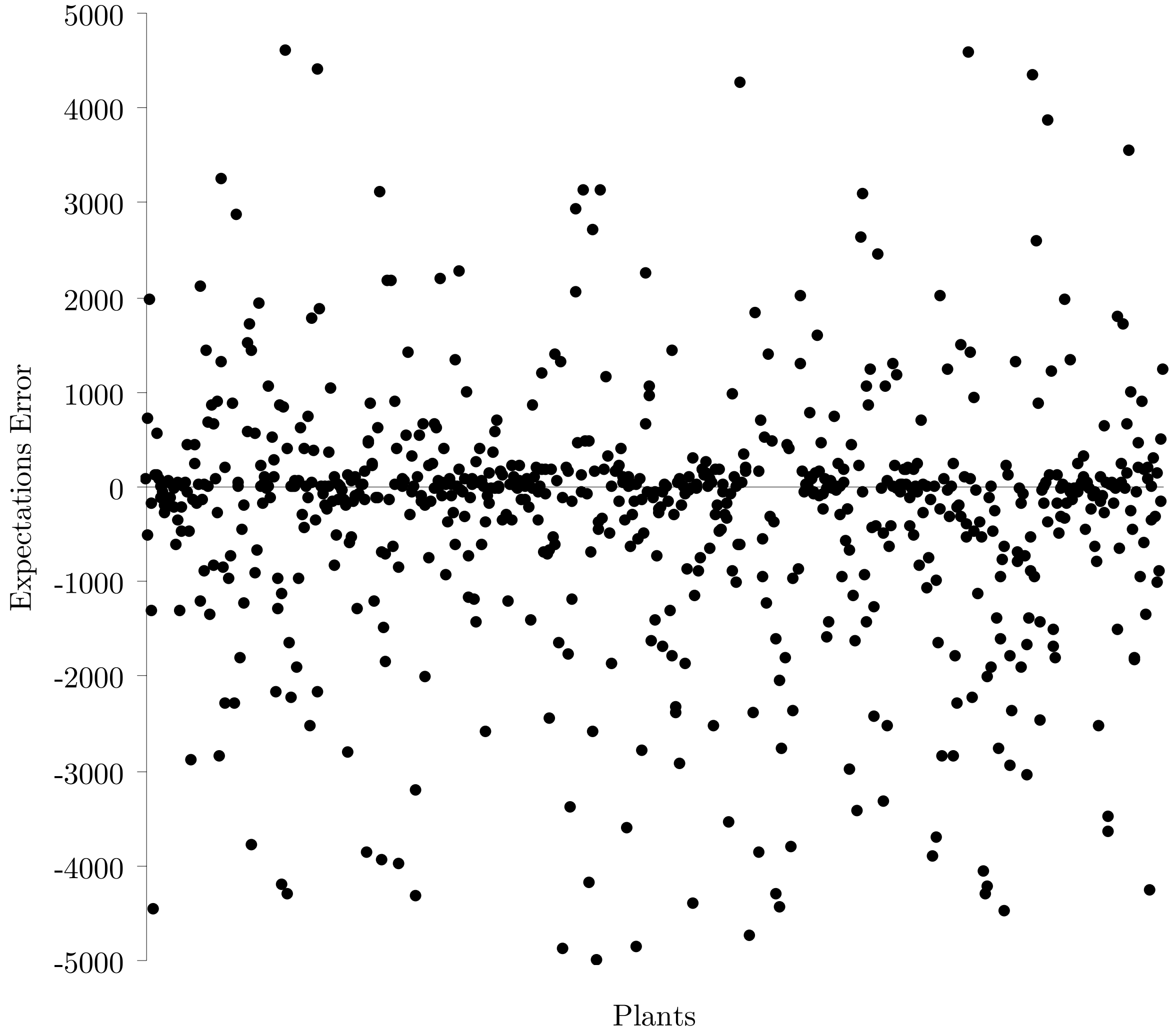

Figure 23: 1989(b), ε_{it} vs. i

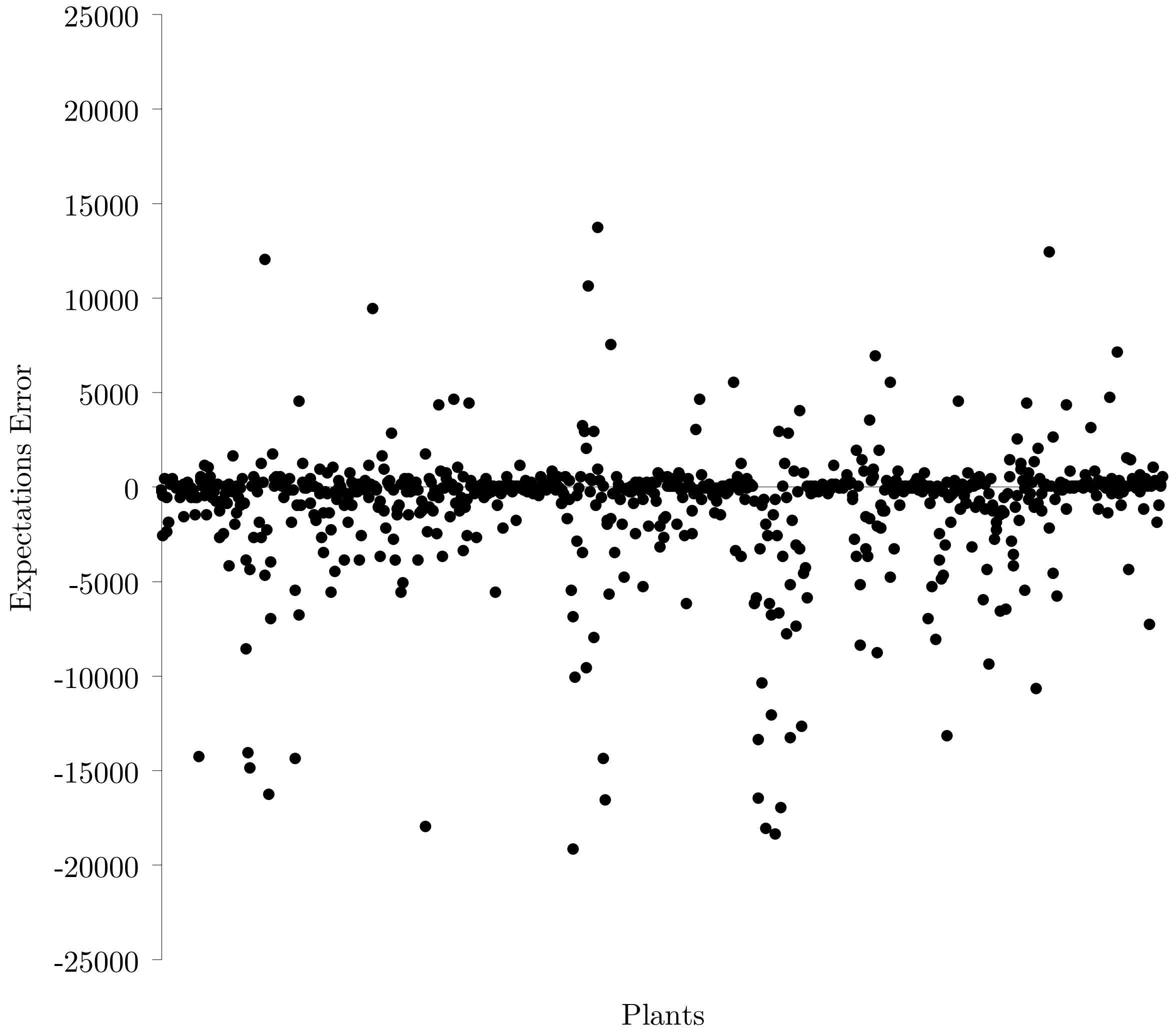

Figure 24: 1990(a), ε_{it} vs. i

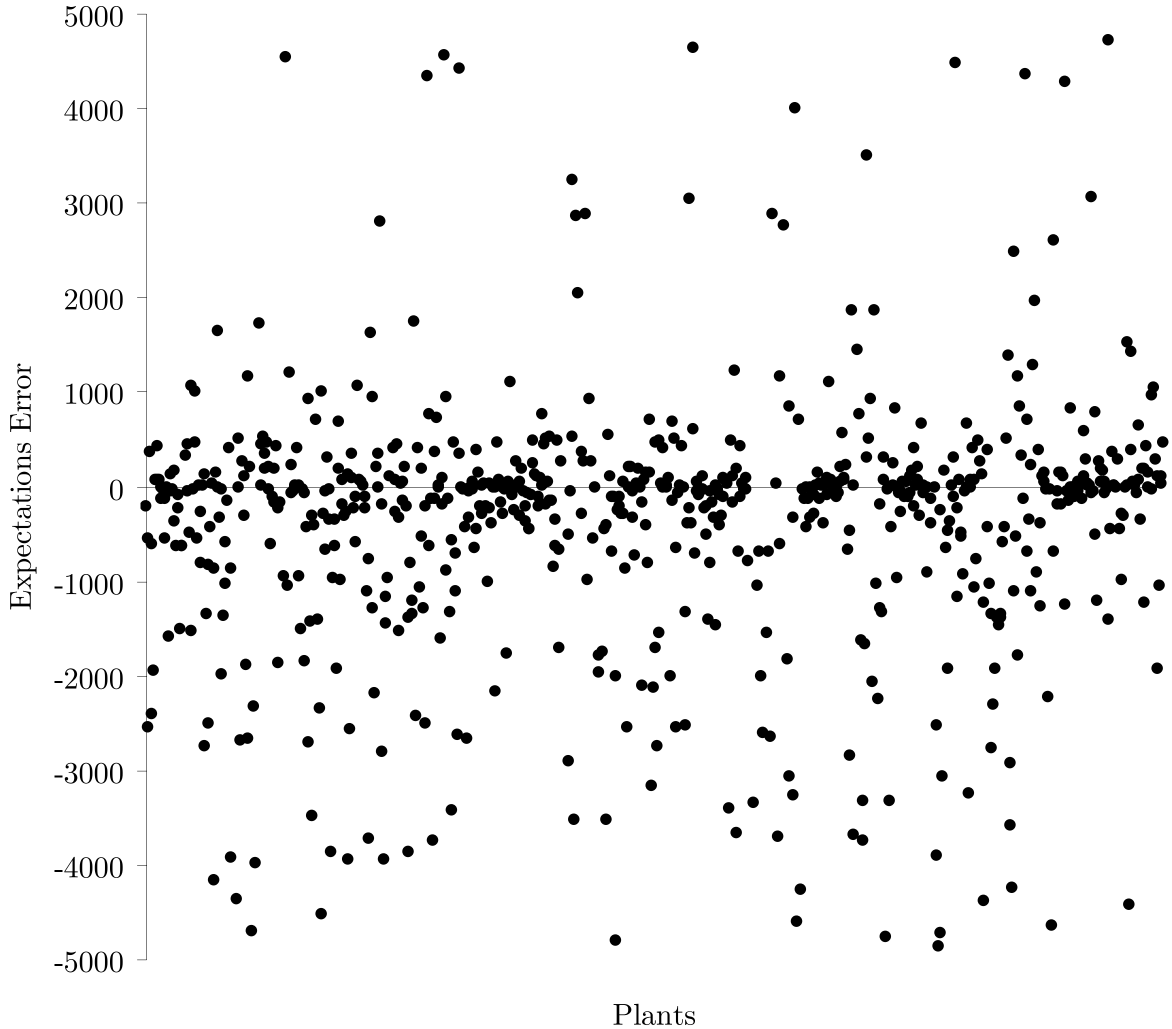

Figure 25: 1990(b), ε_{it} vs. i

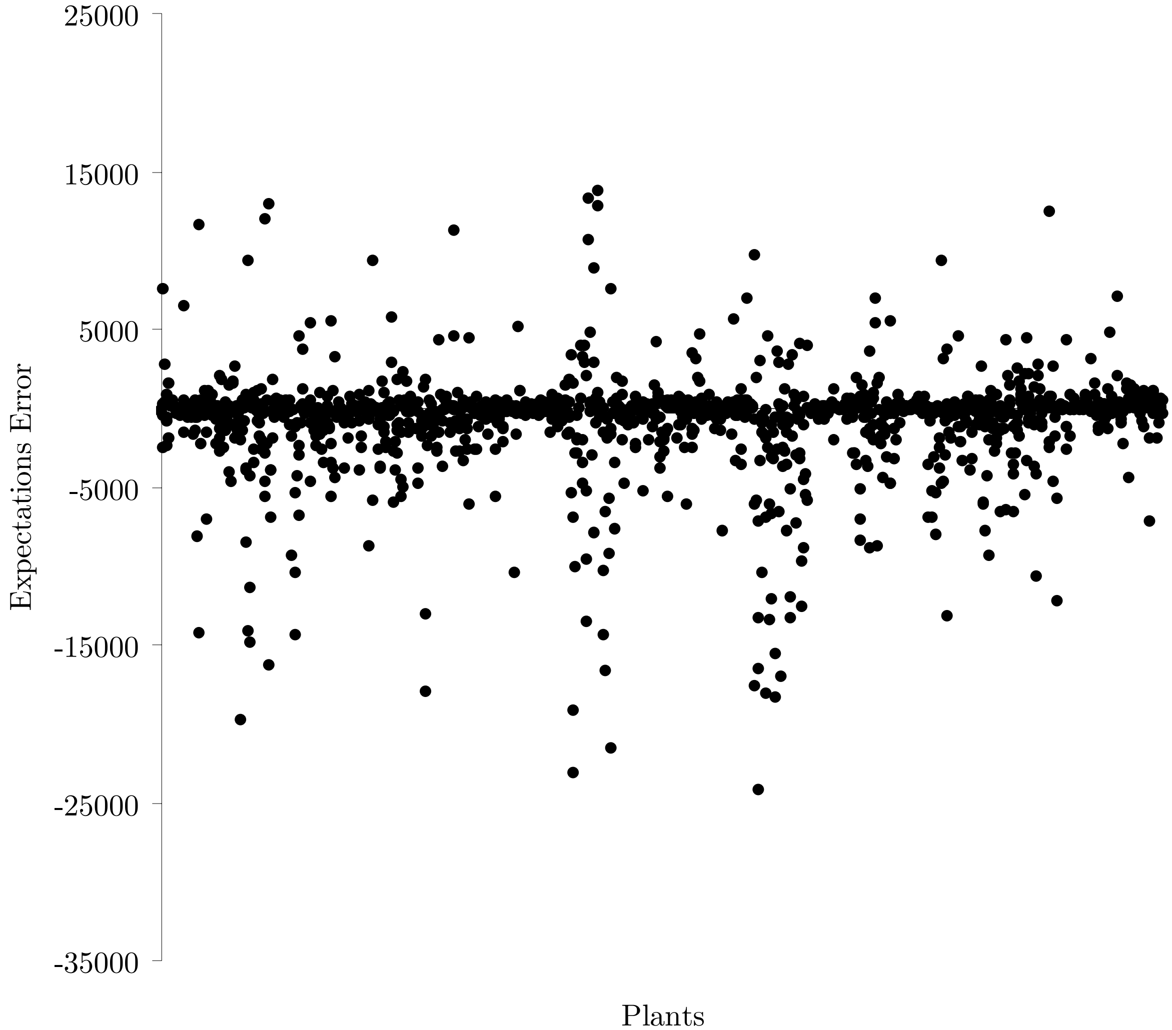

Figure 26: 1991(a), ε_{it} vs. i

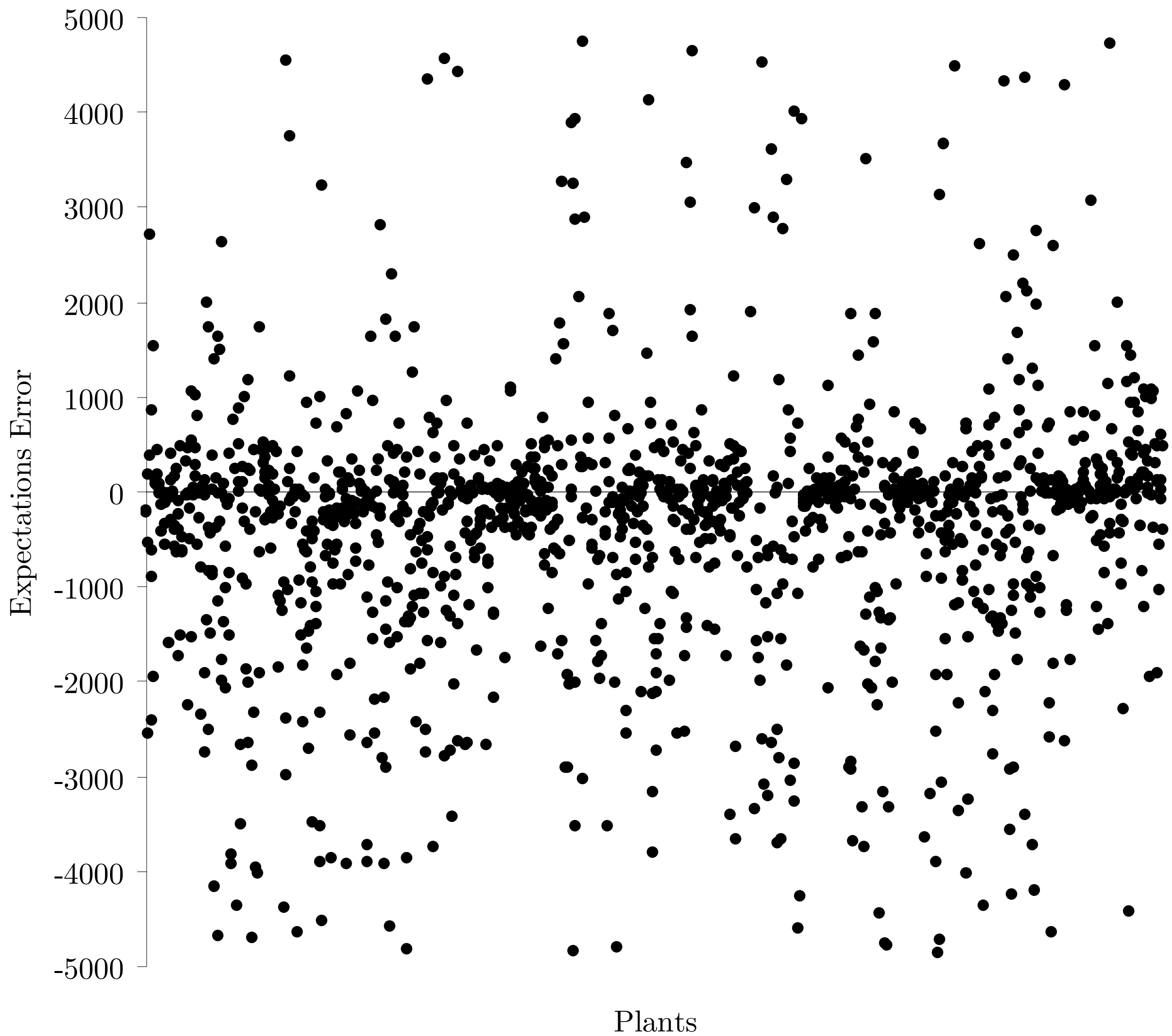

Figure 27: 1991(b), ε_{it} vs. i

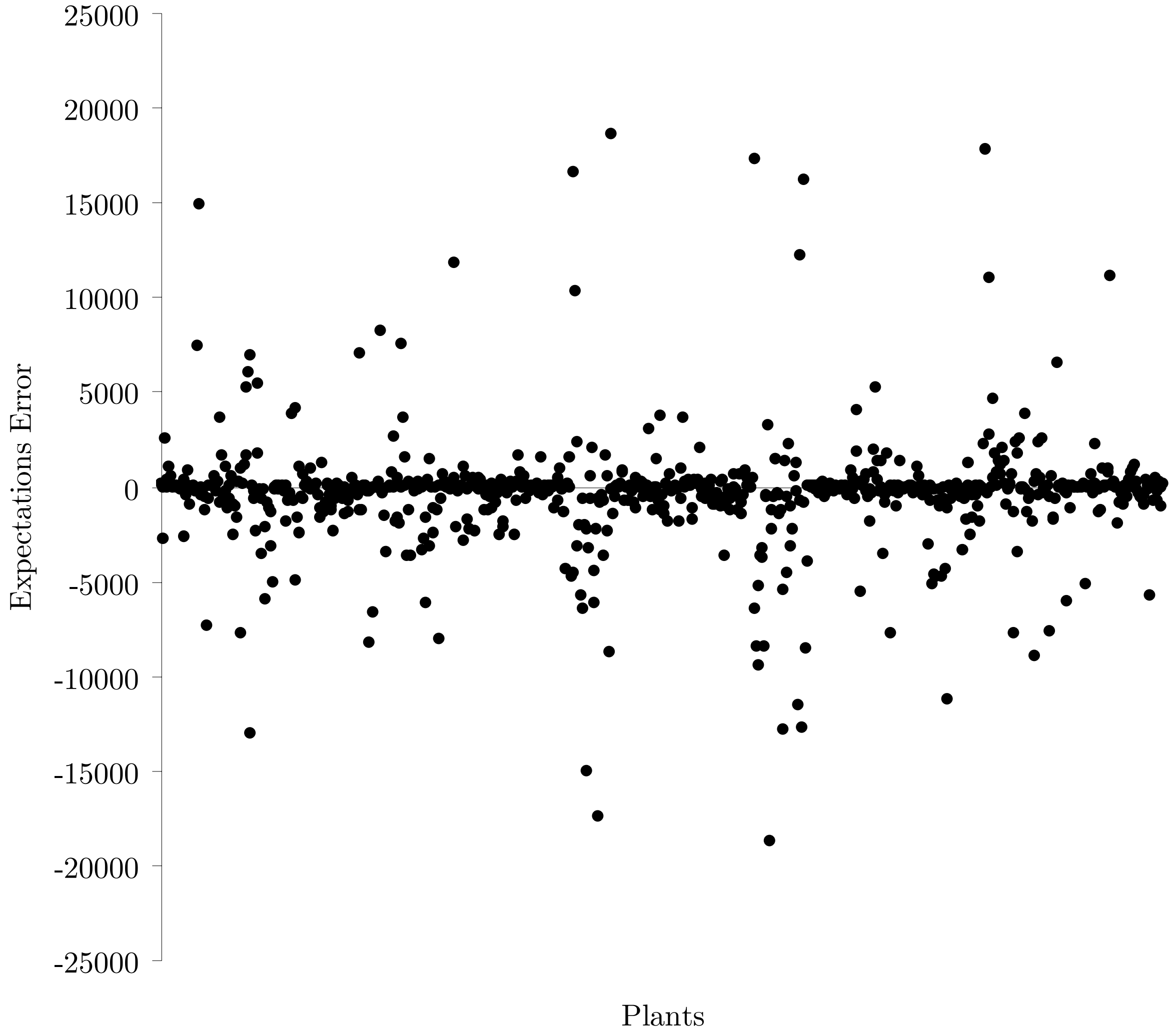

Figure 28: 1992(a), ε_{it} vs. i

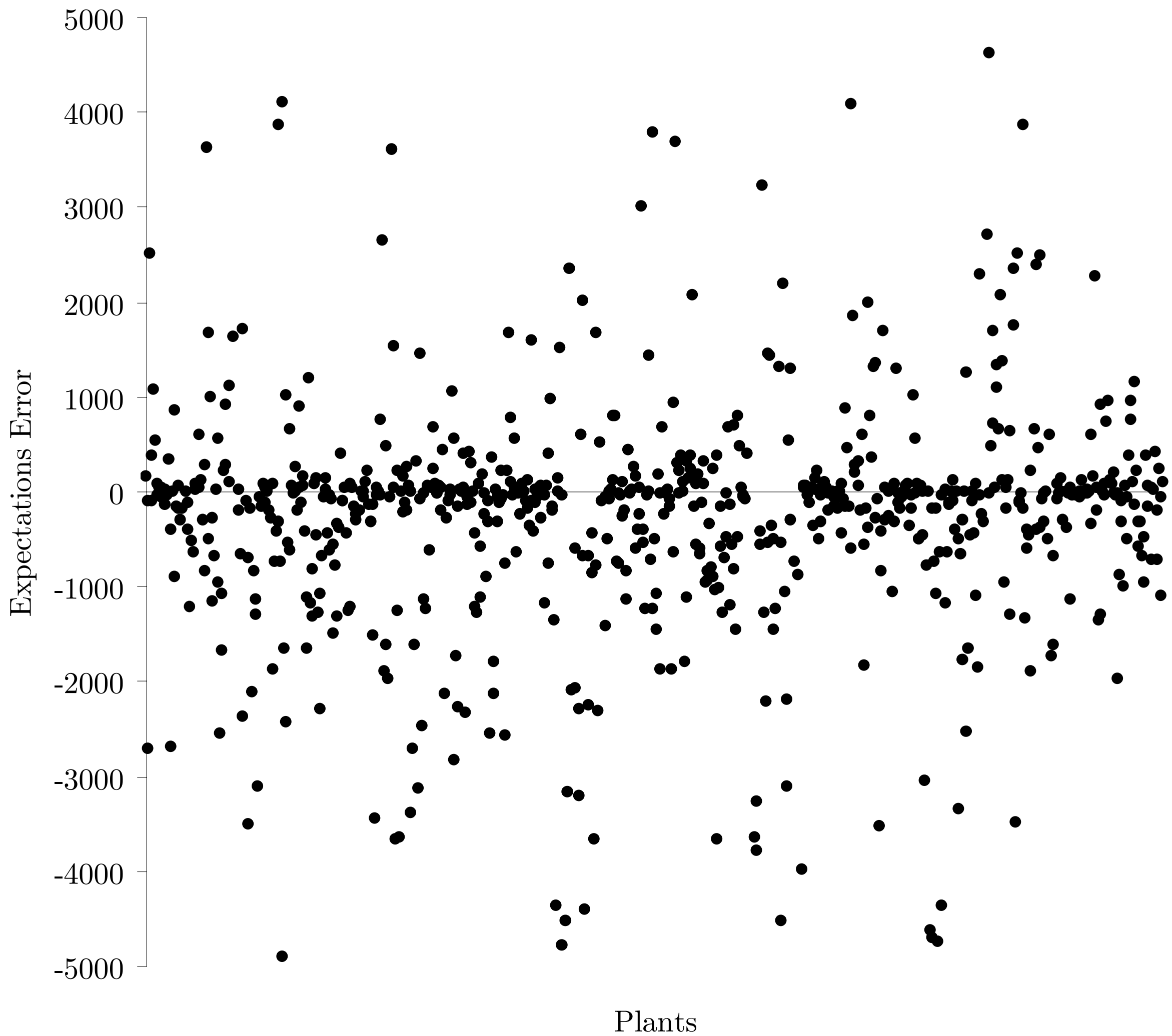

Figure 29: 1992(b), ε_{it} vs. i

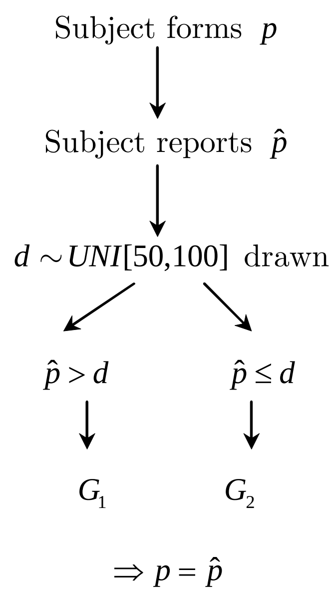

Figure 30: Payoffs

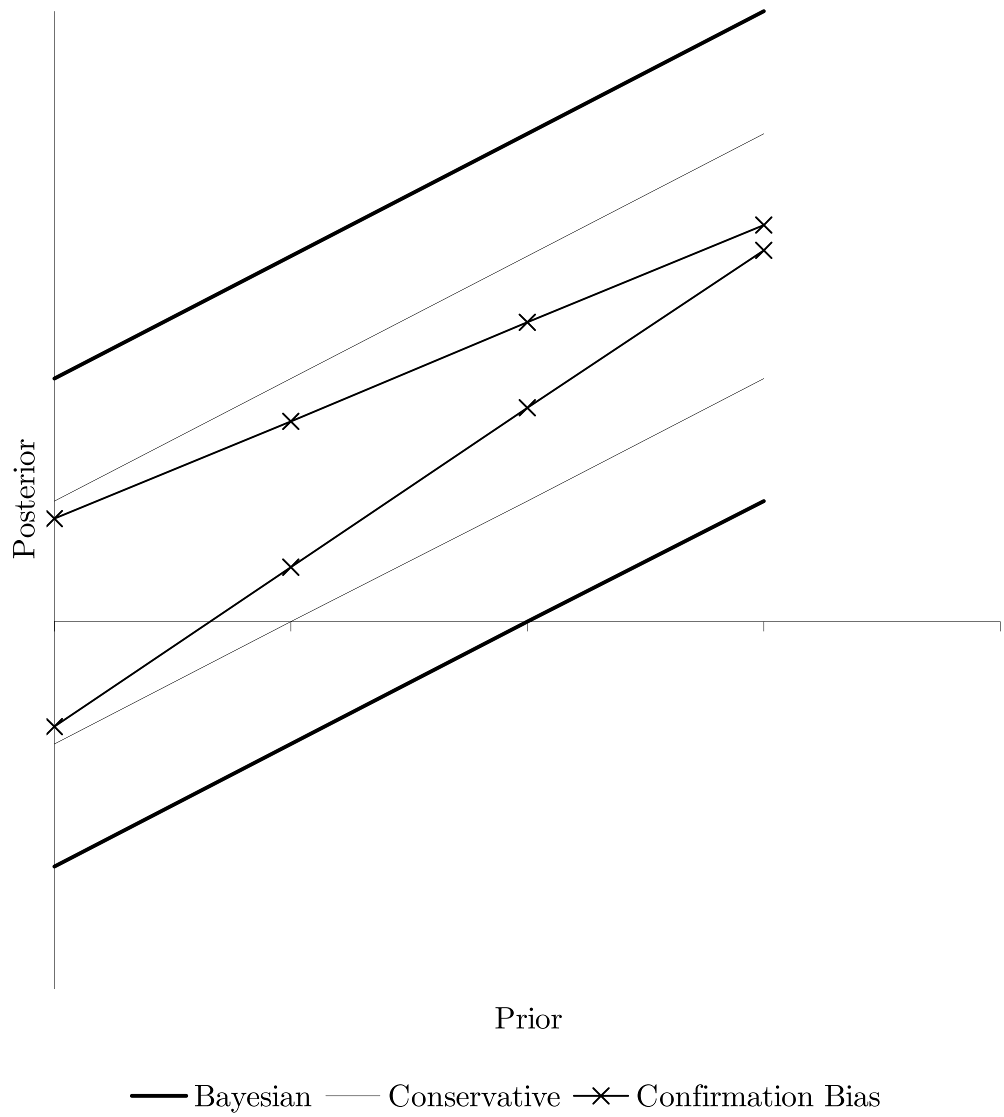

Figure 31: Theoretical Regression Lines

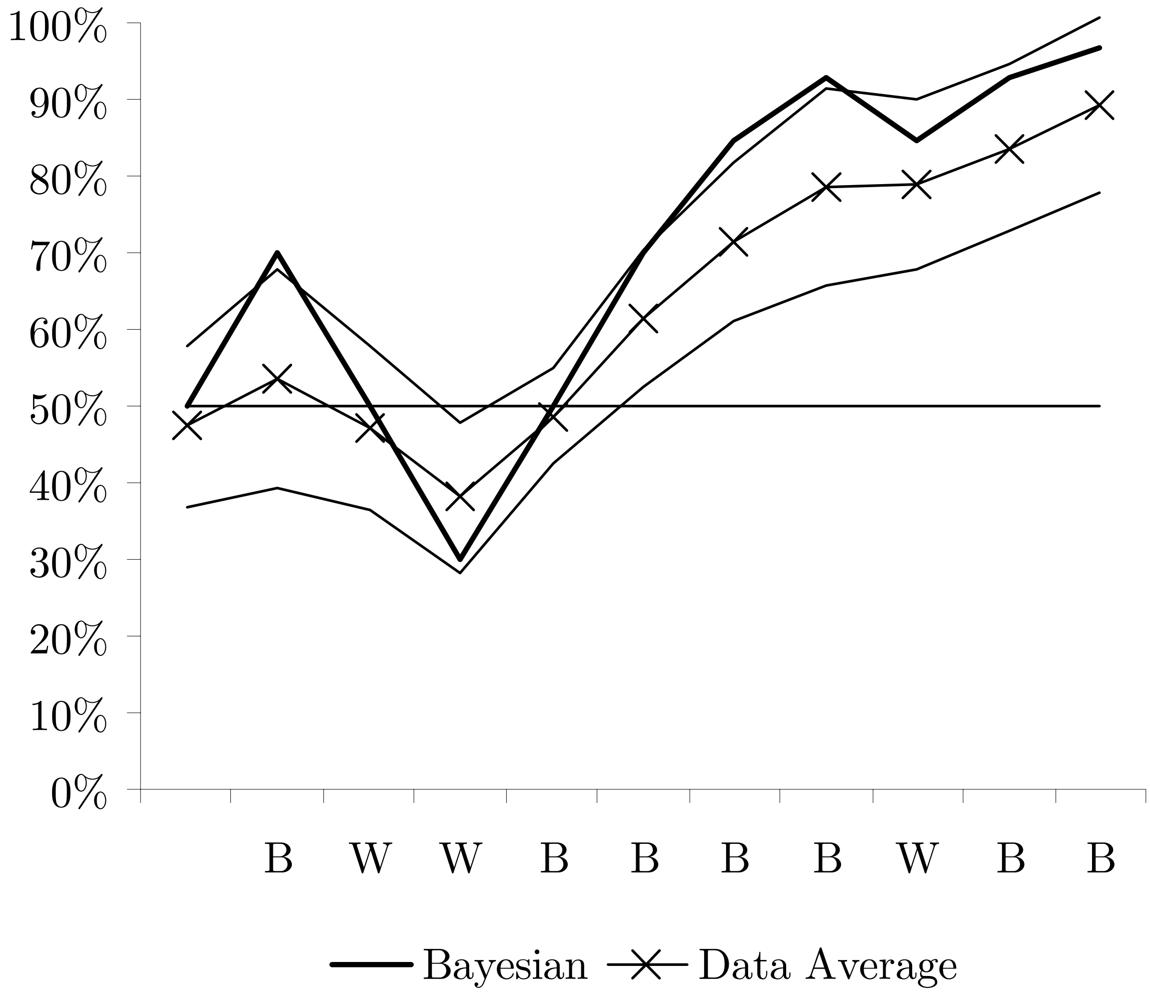

Figure 32: Treatment A, Round 1

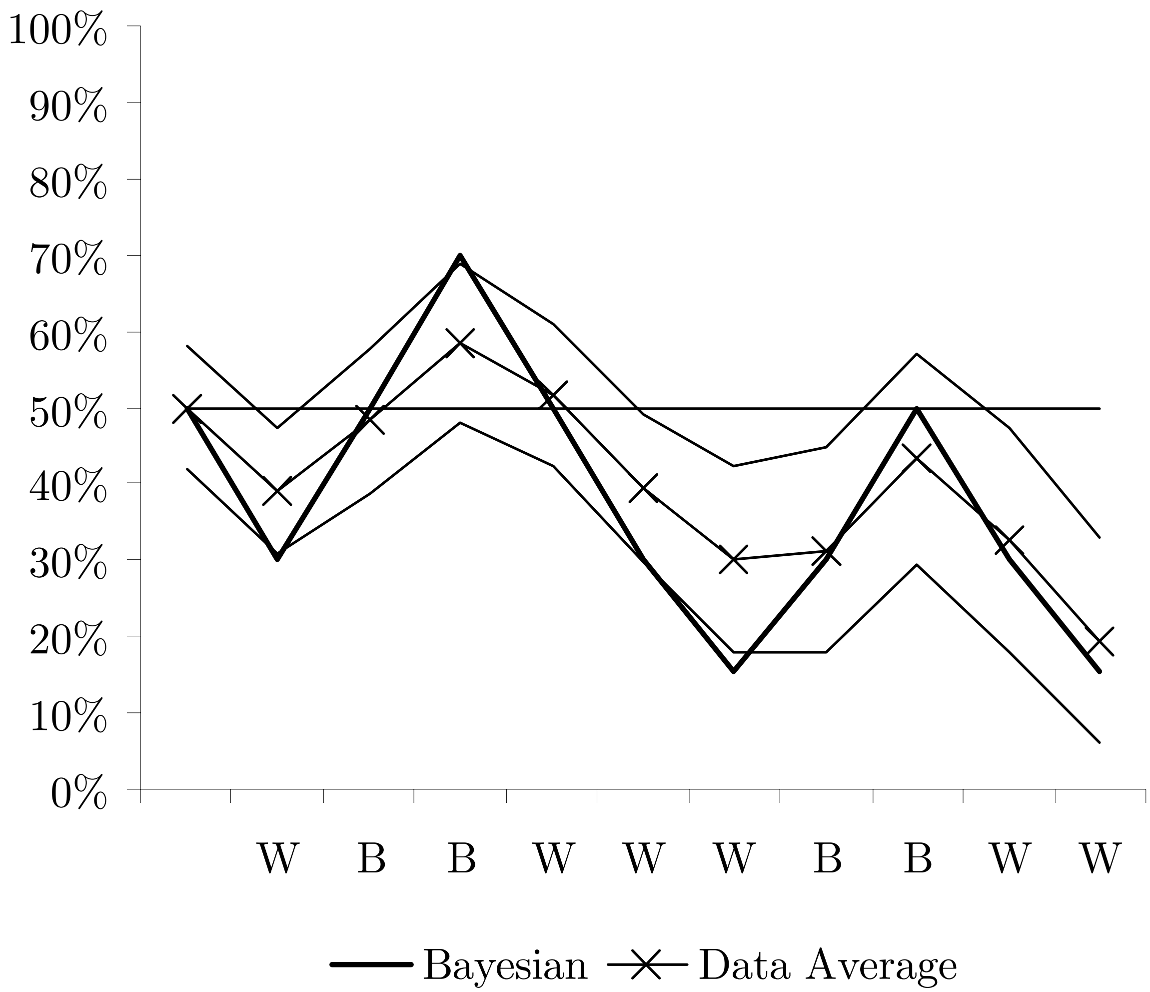

Figure 33: Treatment A, Round 2

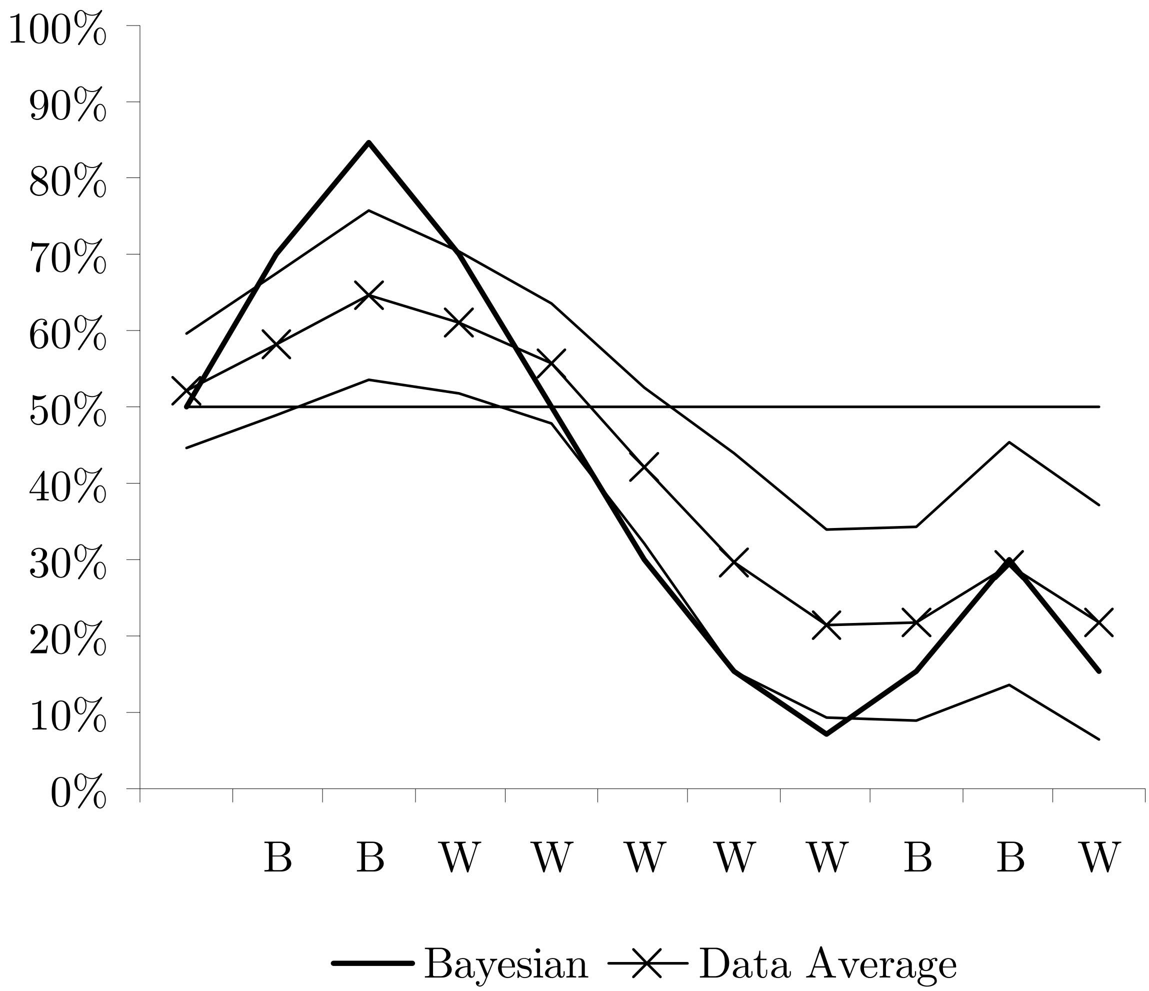

Figure 34: Treatment A, Round 3

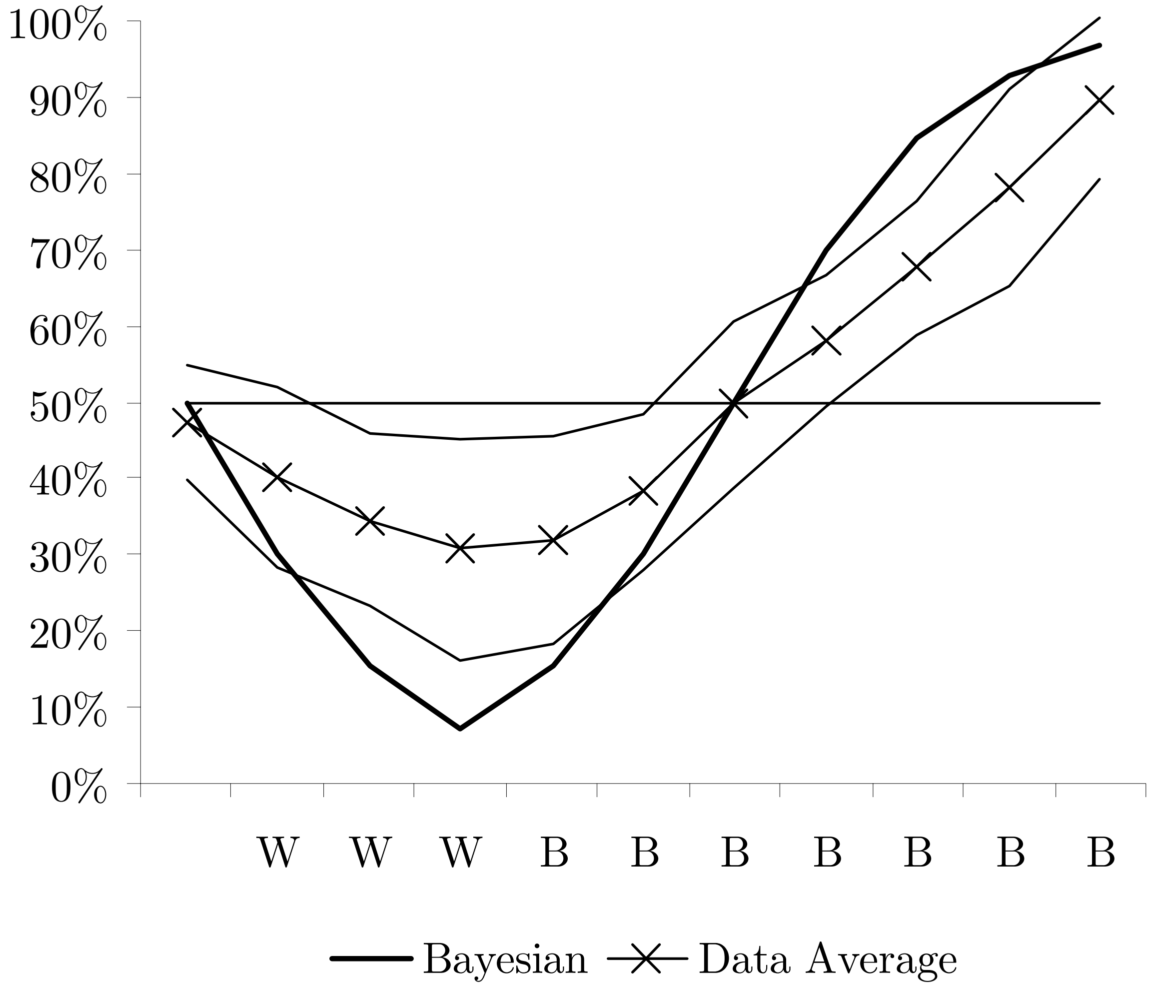

Figure 35: Treatment A, Round 4

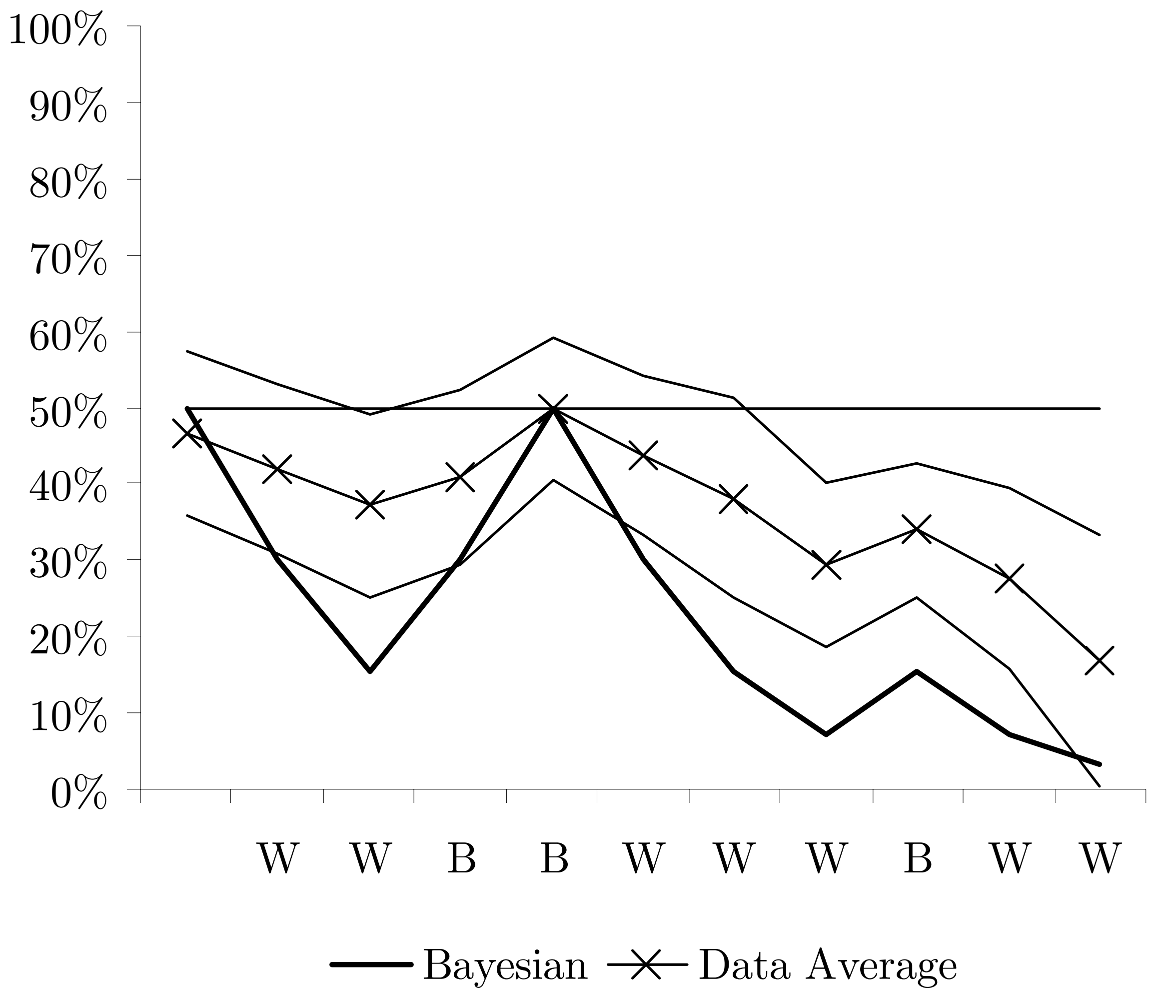

Figure 36: Treatment A, Round 5

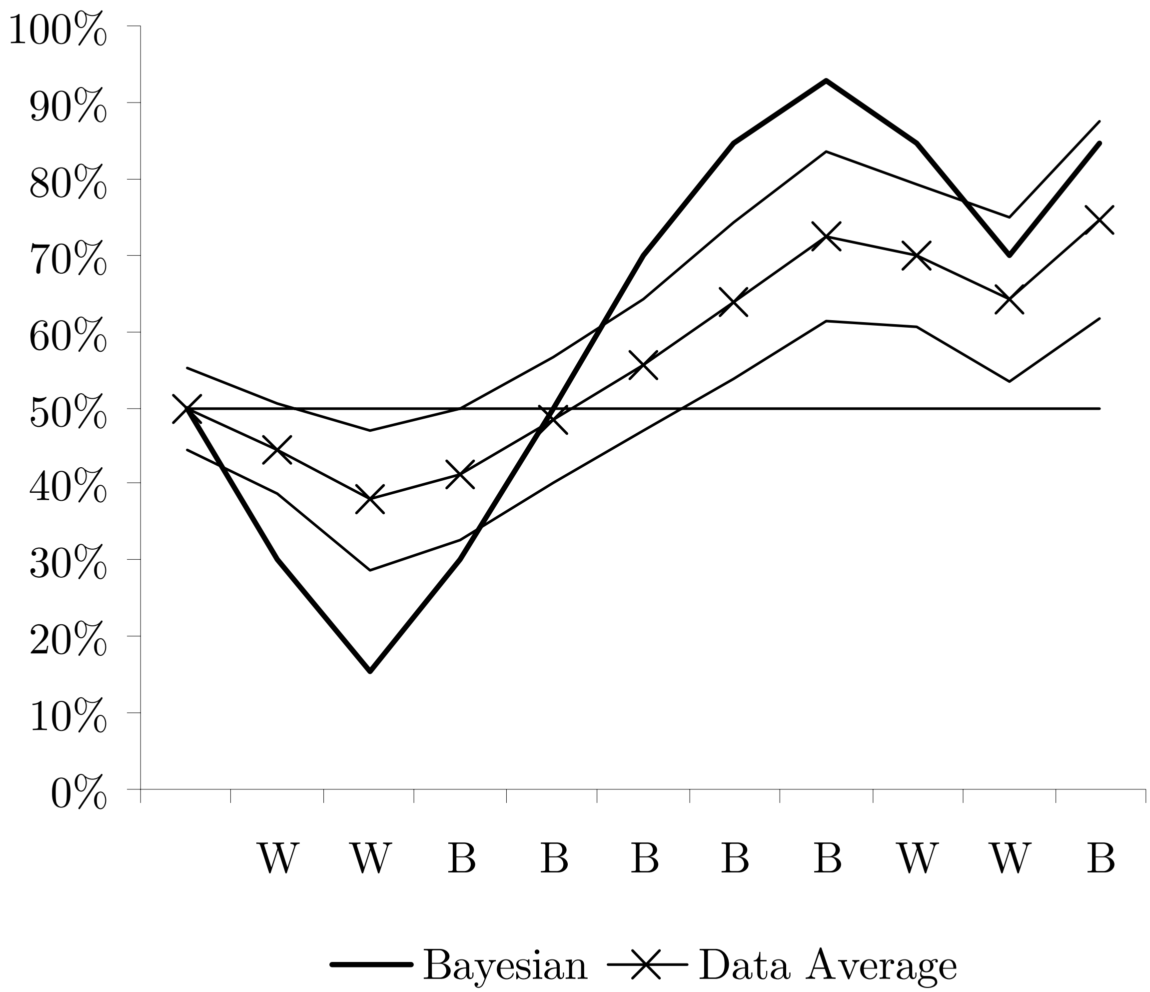

Figure 37: Treatment A, Round 6

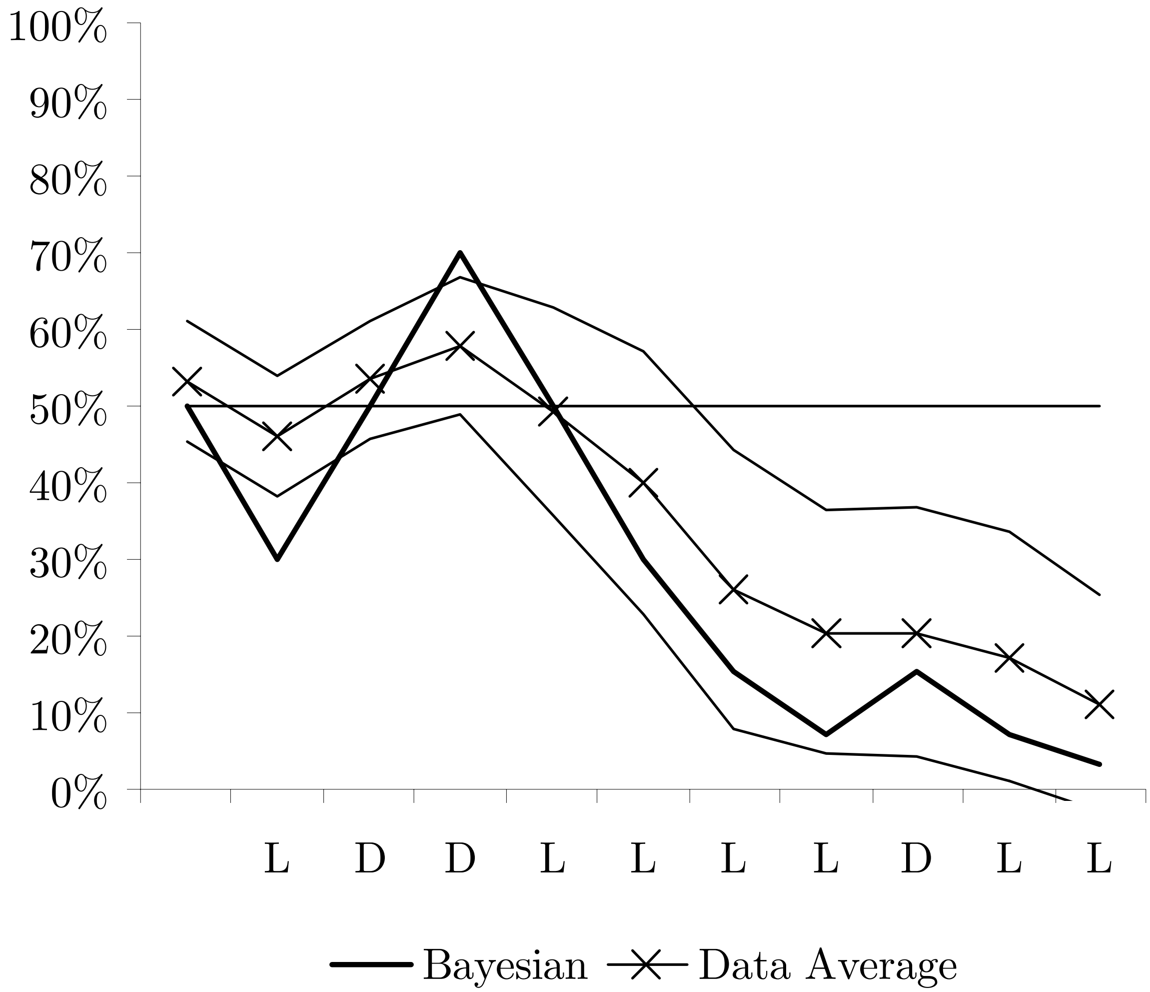

Figure 38: Treatment C, Round 1

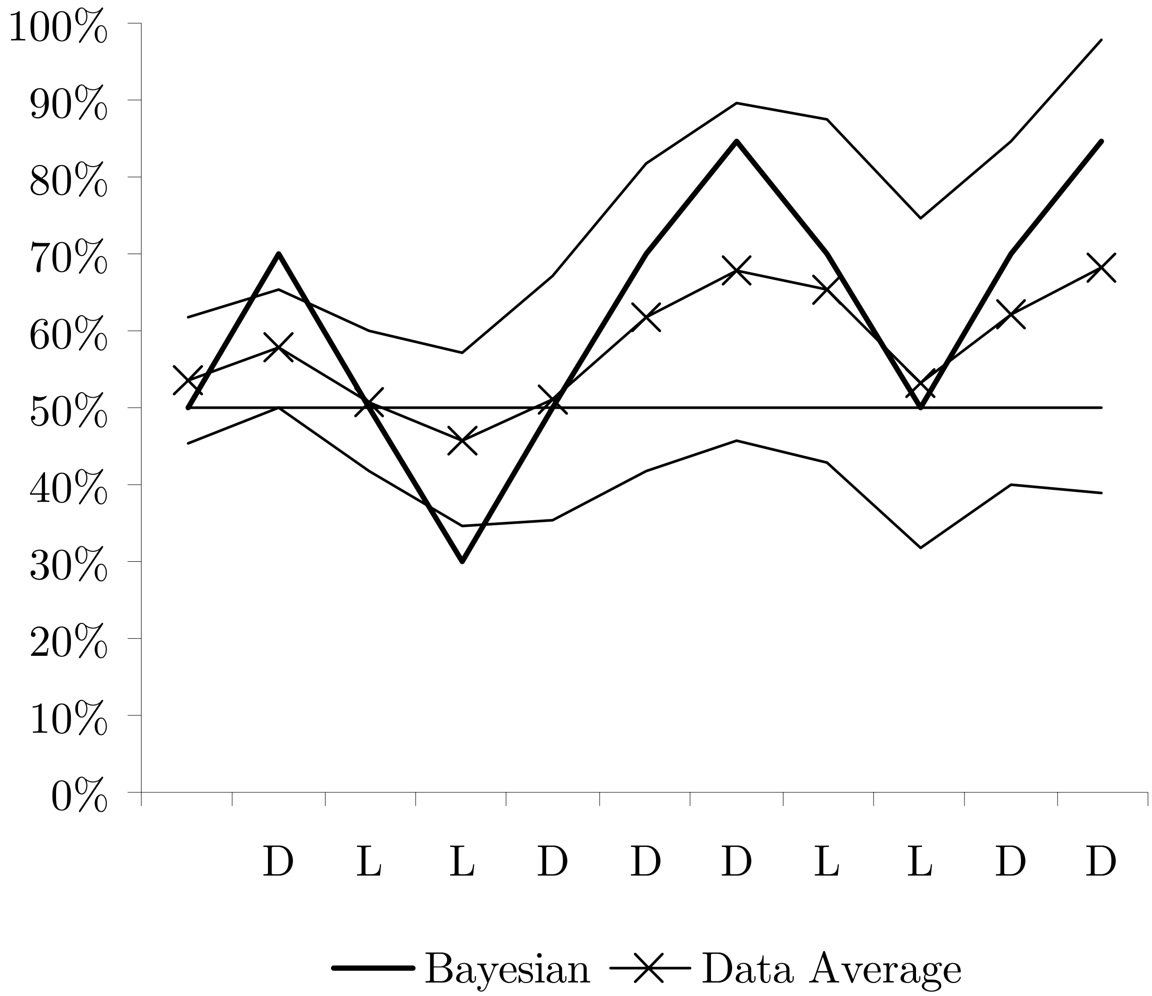

Figure 39: Treatment C, Round 2

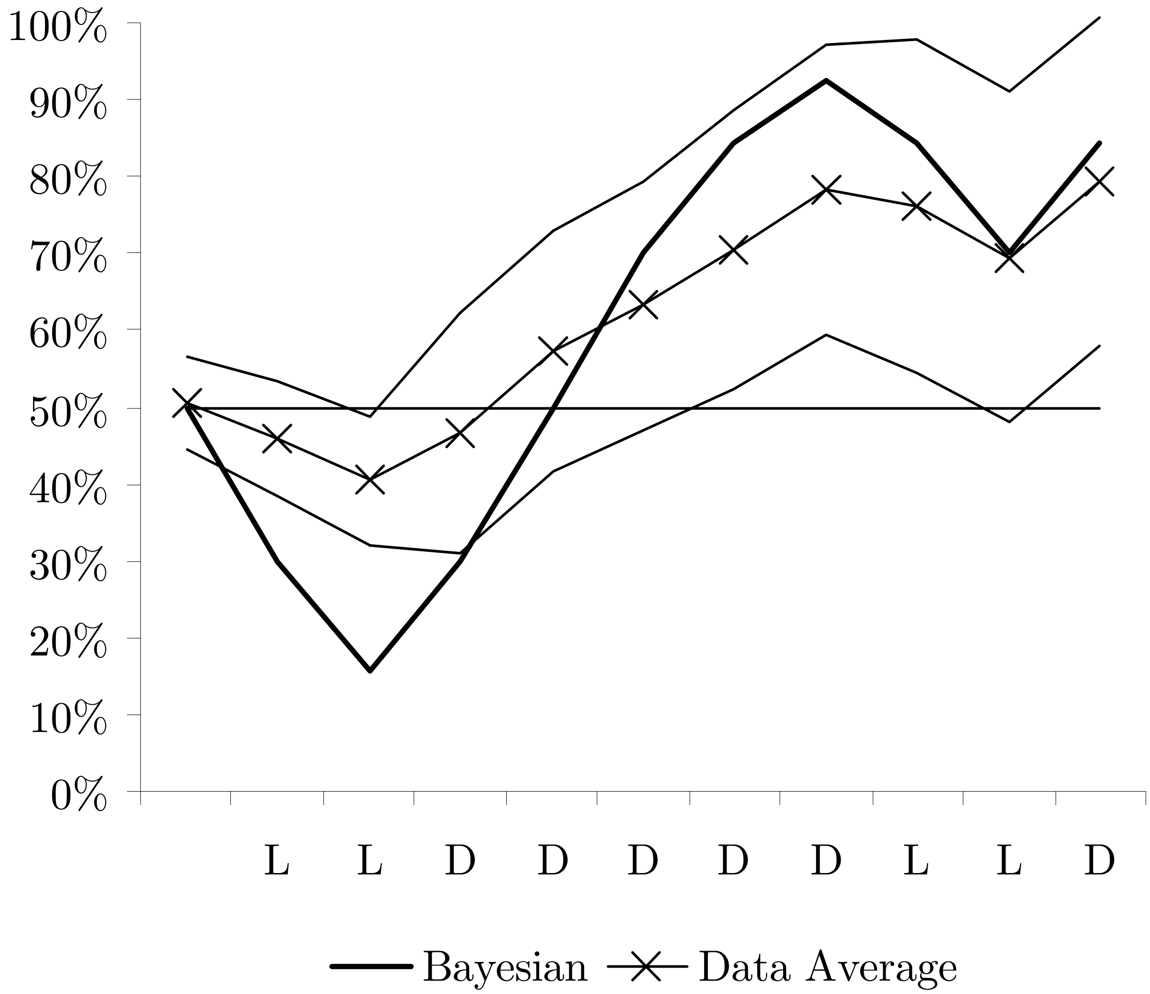

Figure 40: Treatment C, Round 3

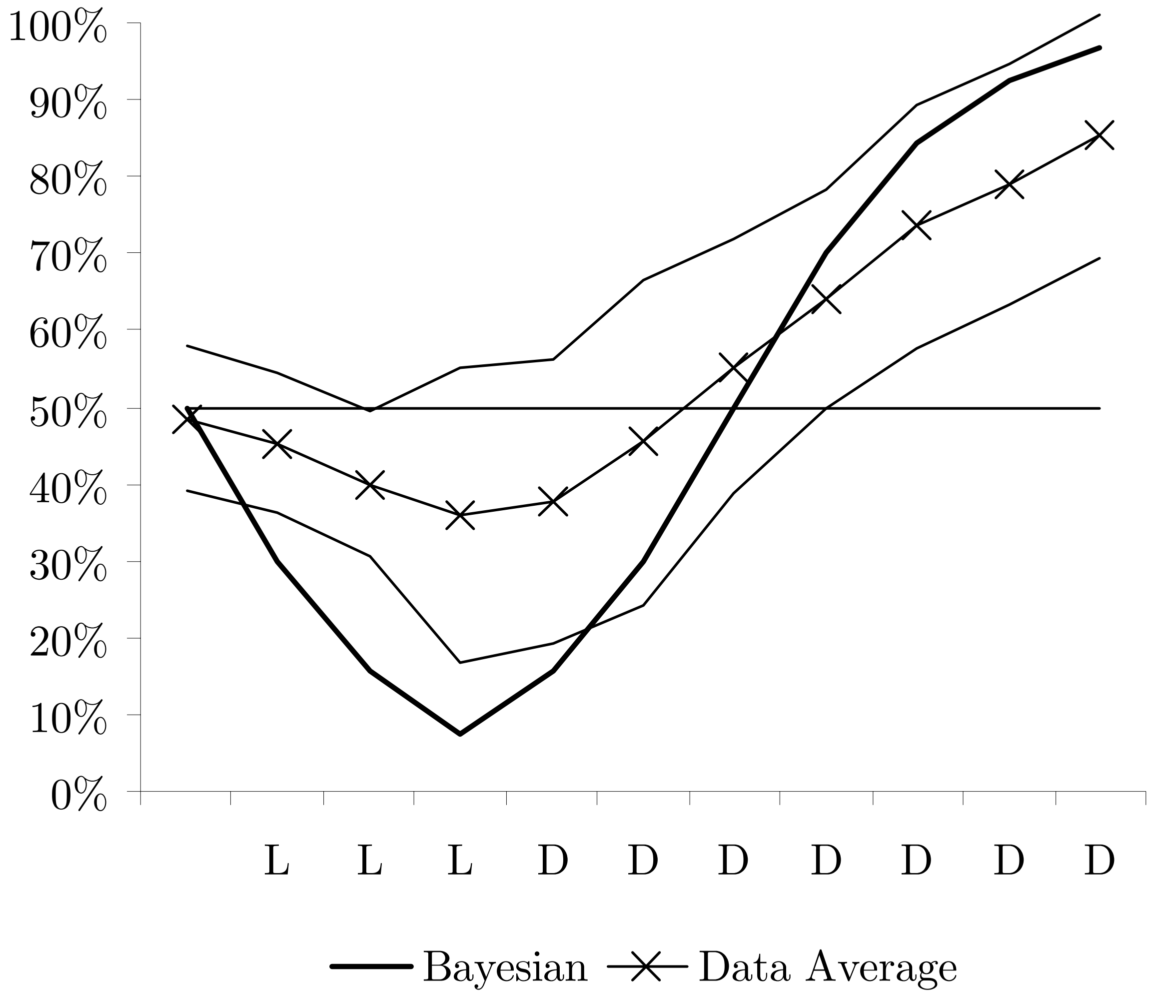

Figure 41: Treatment C, Round 4

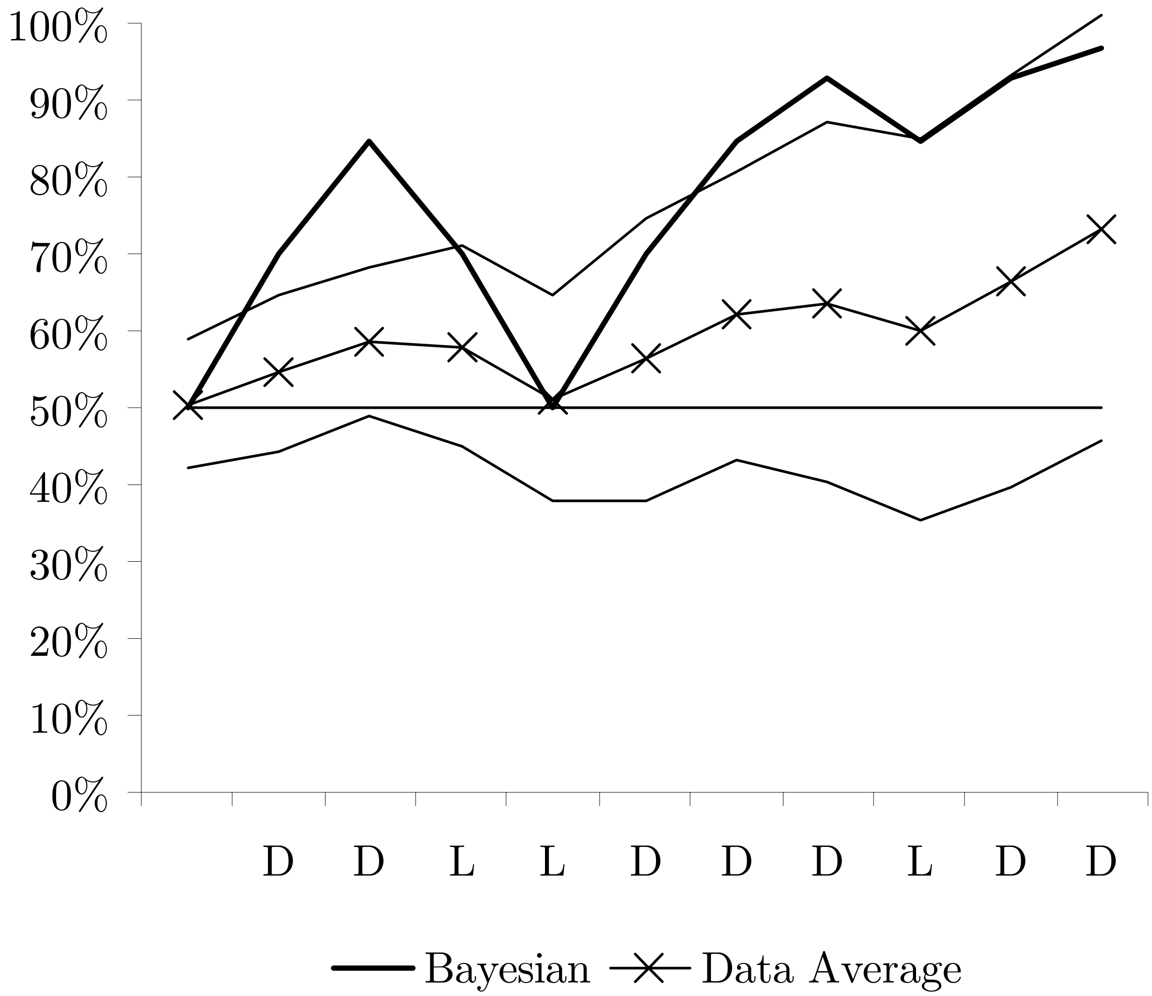

Figure 42: Treatment C, Round 5

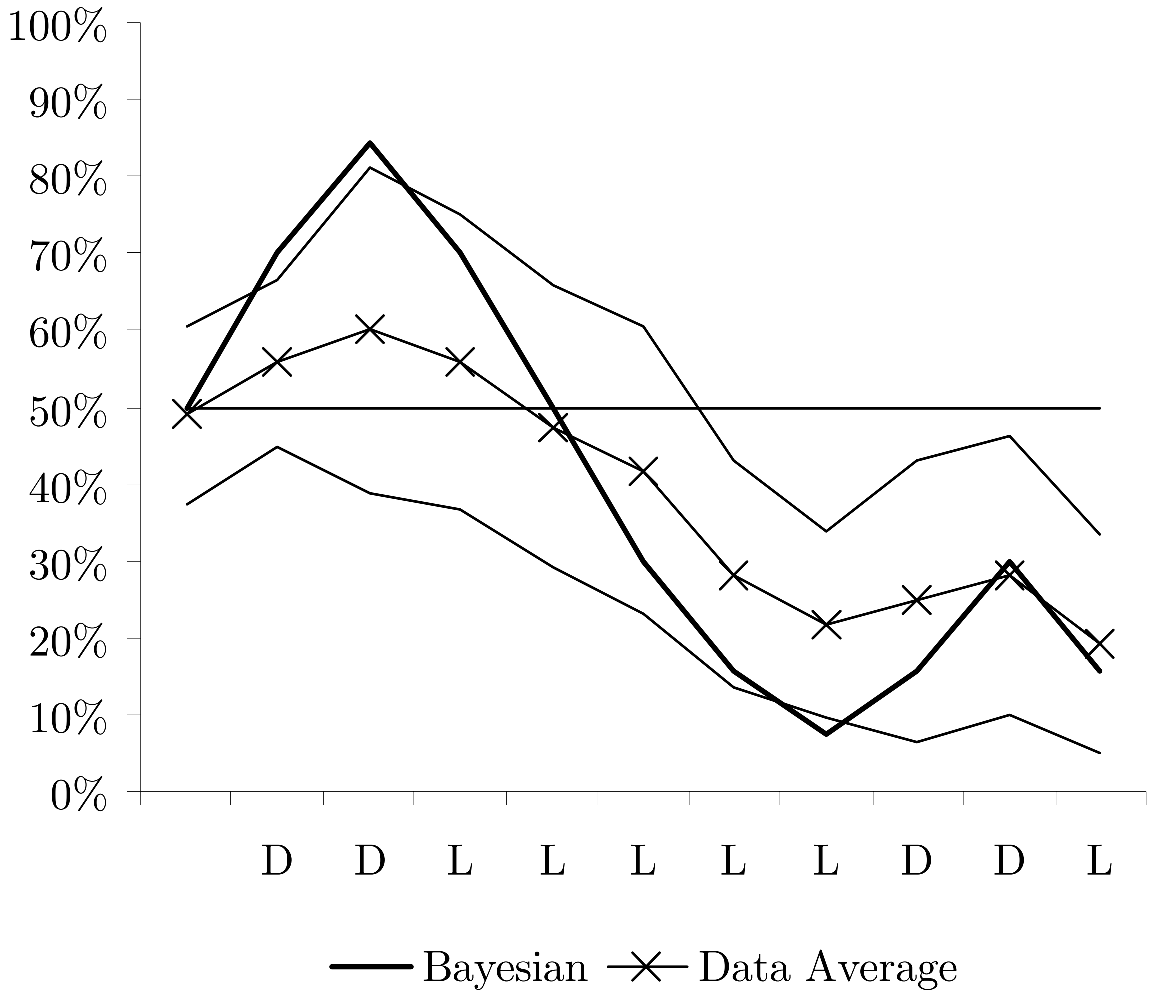

Figure 43: Treatment C, Round 6

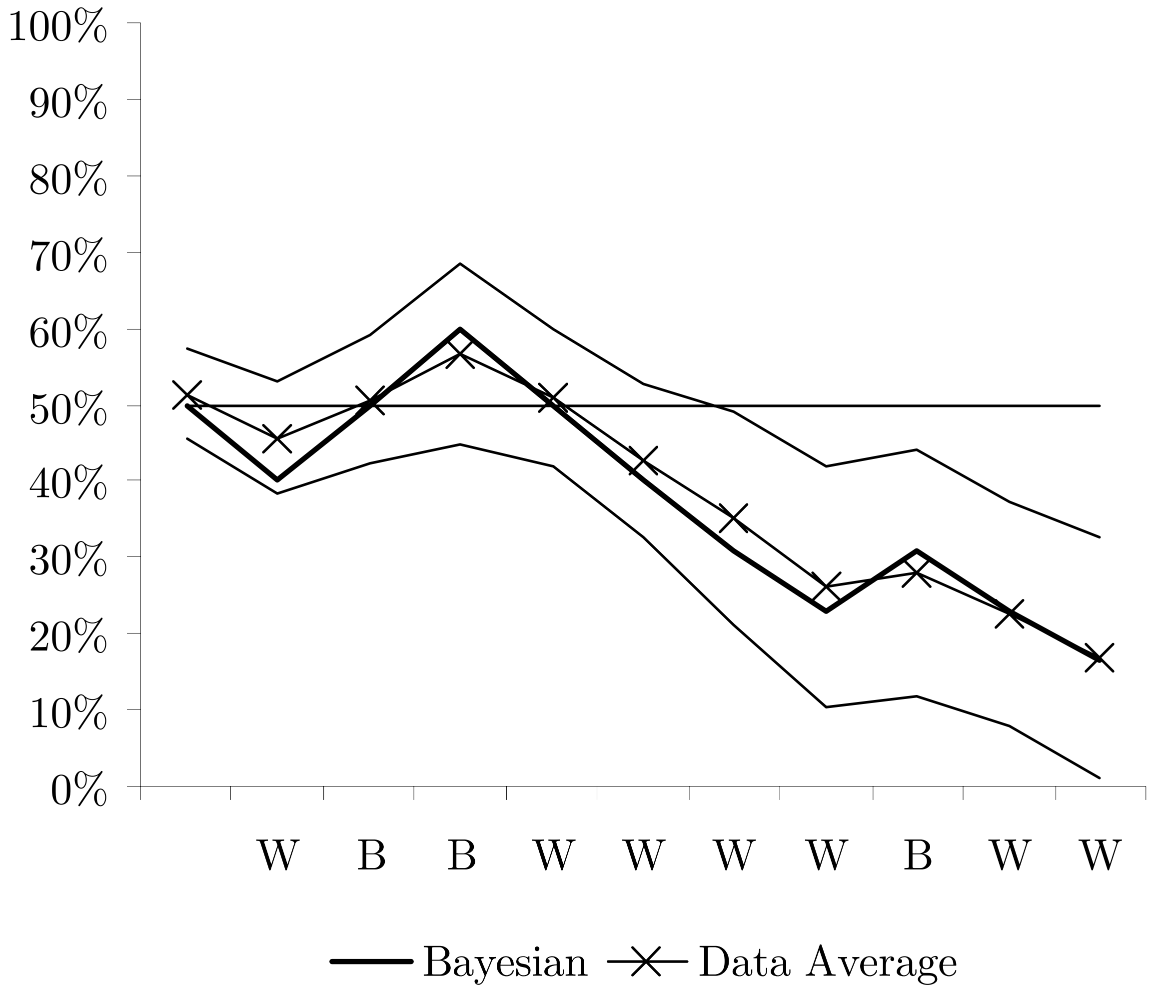

Figure 44: Treatment B, Round 1

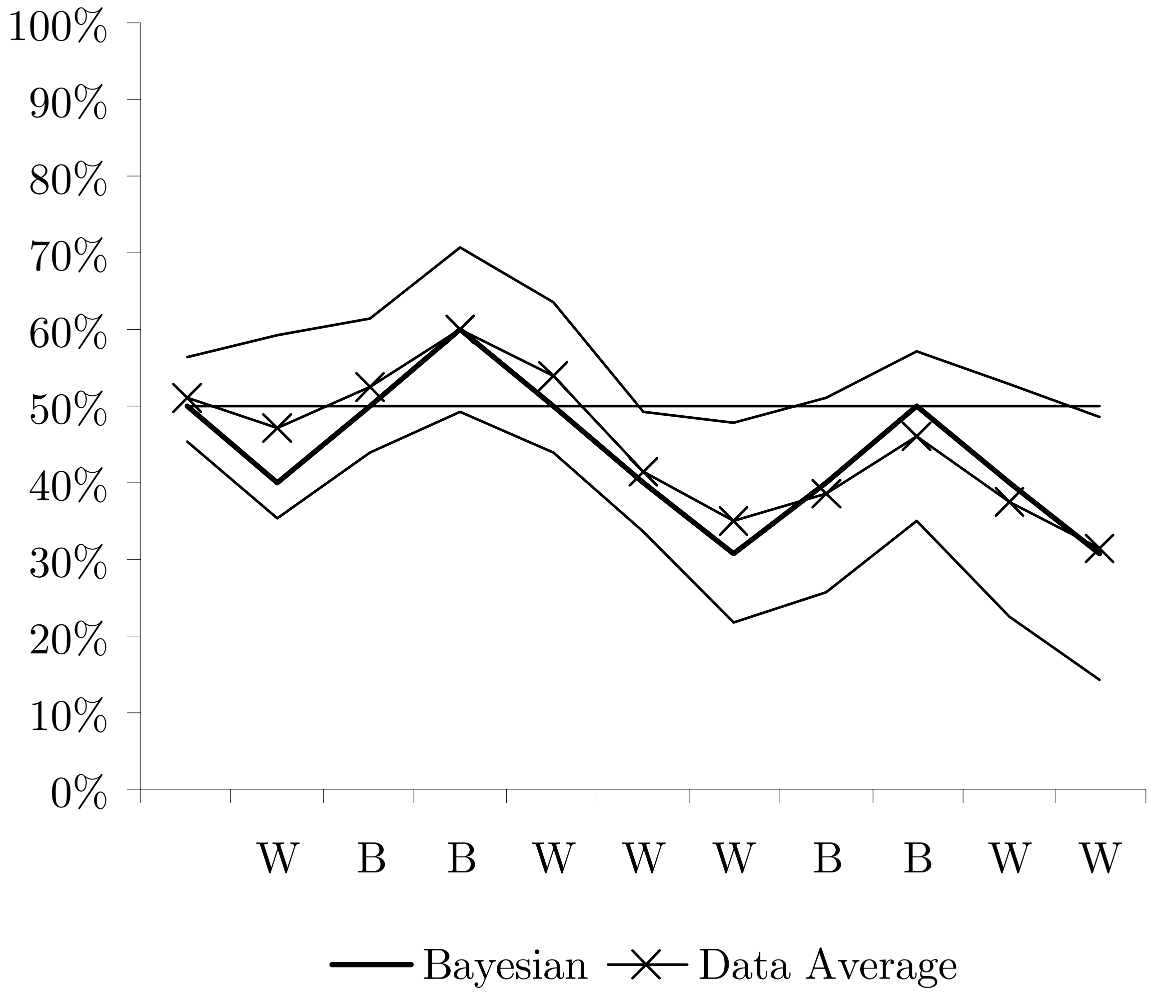

Figure 45: Treatment B, Round 2

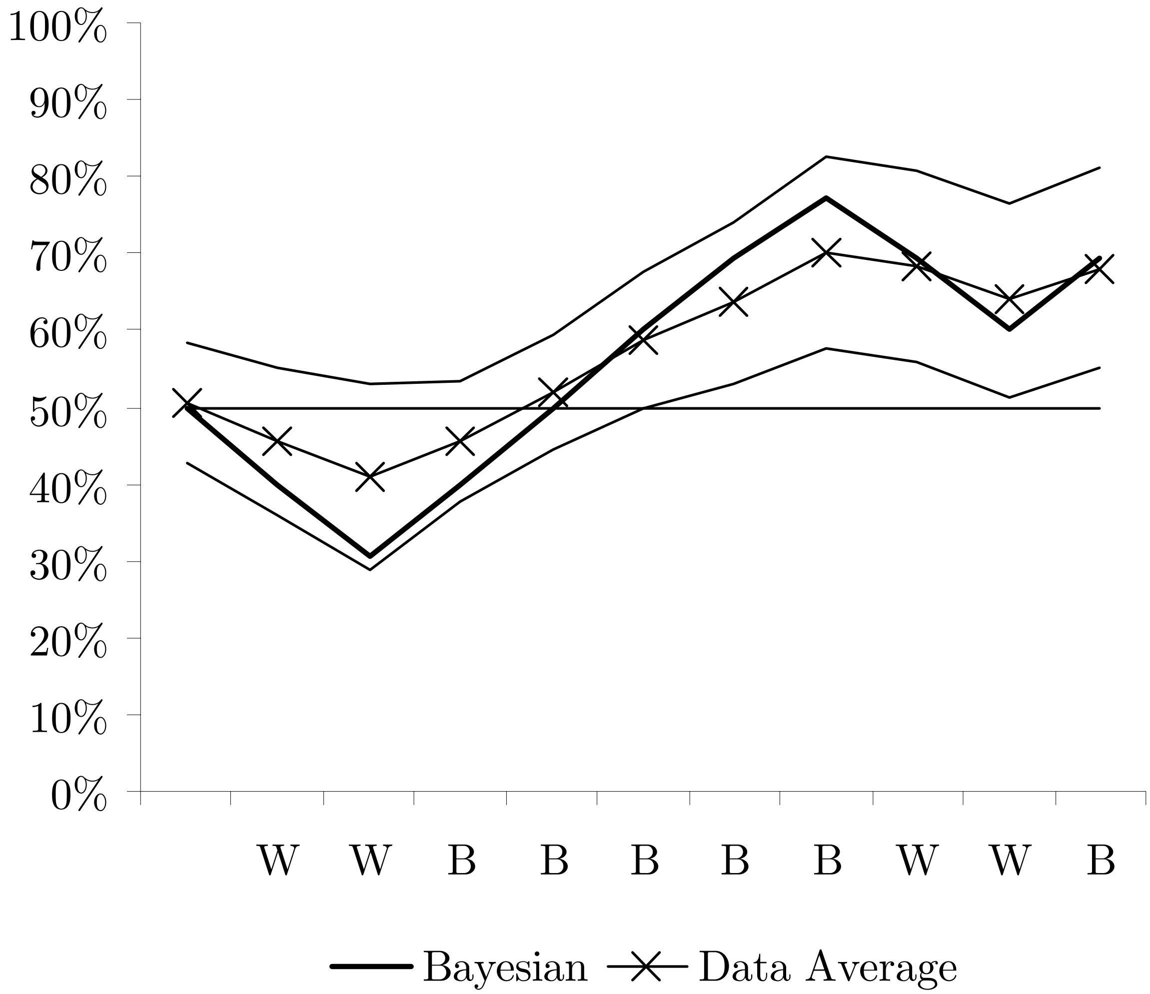

Figure 46: Treatment B, Round 3

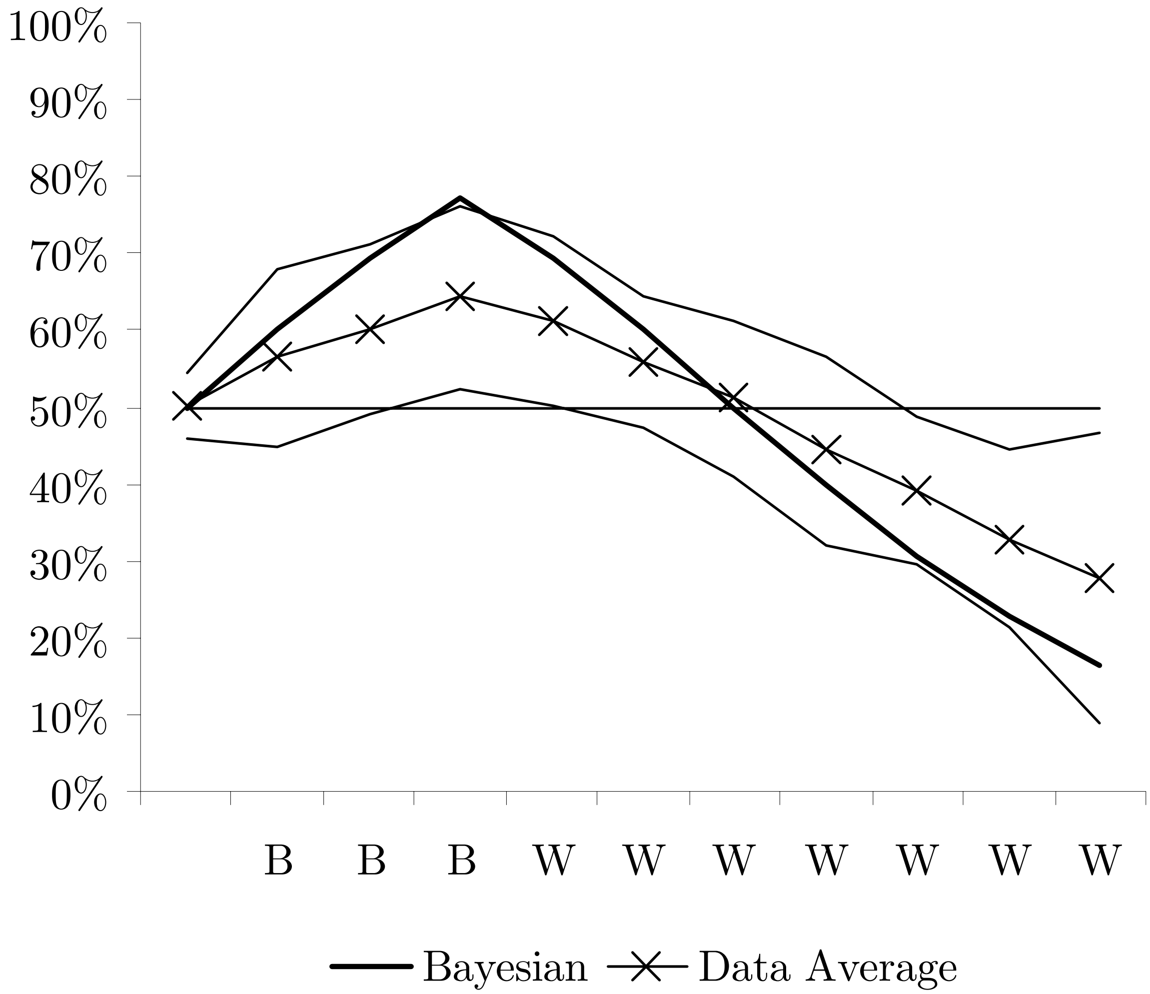

Figure 47: Treatment B, Round 4

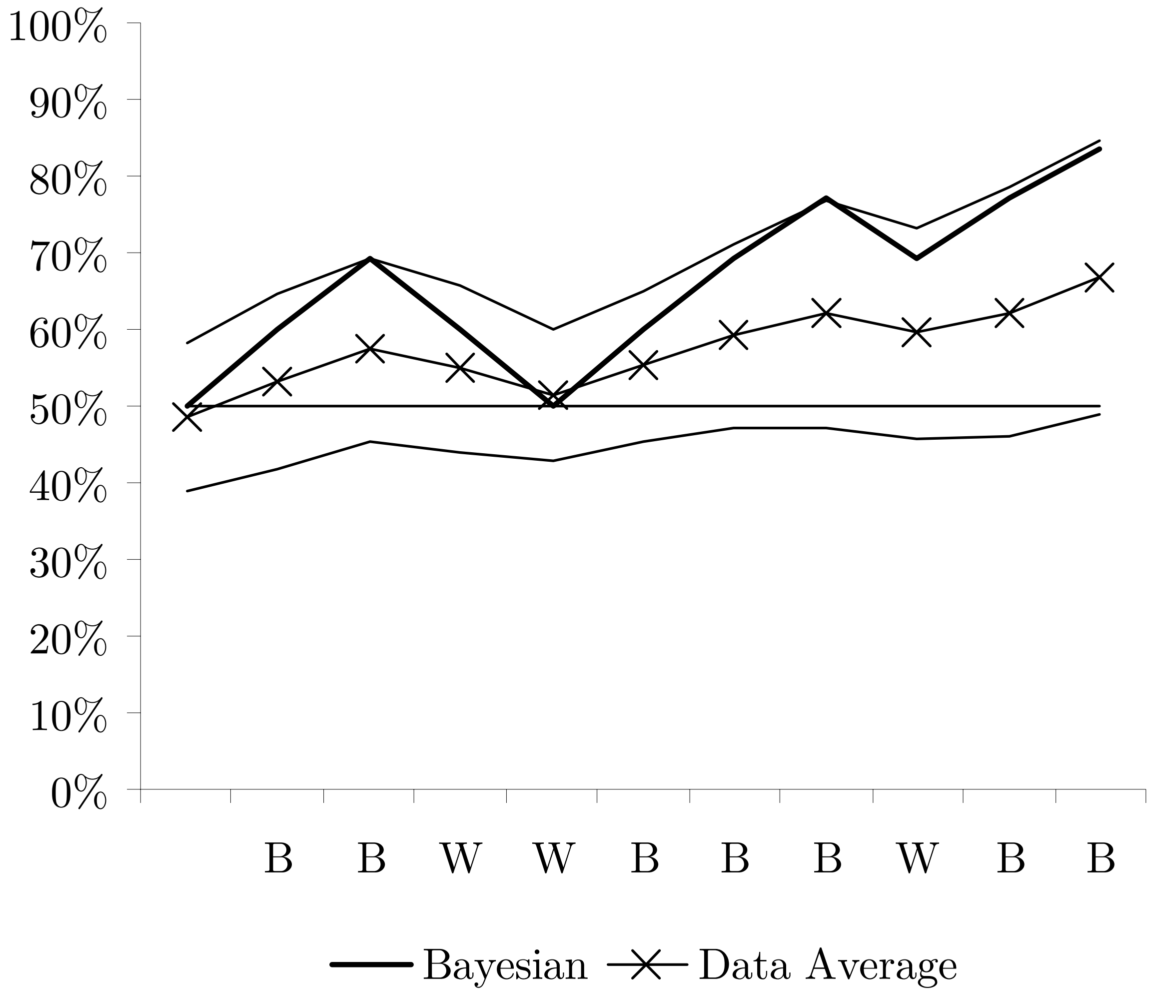

Figure 48: Treatment B, Round 5

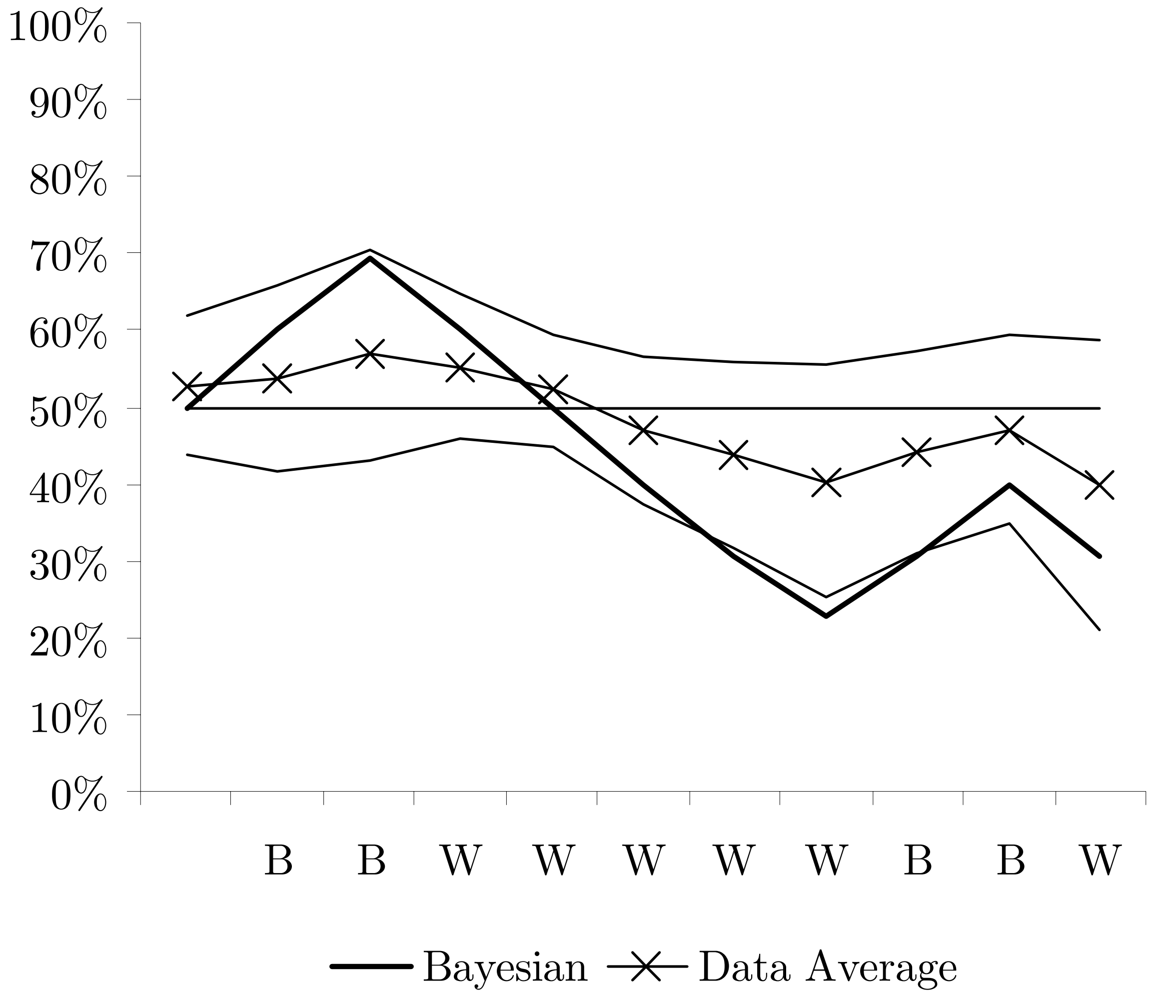

Figure 49: Treatment B, Round 6

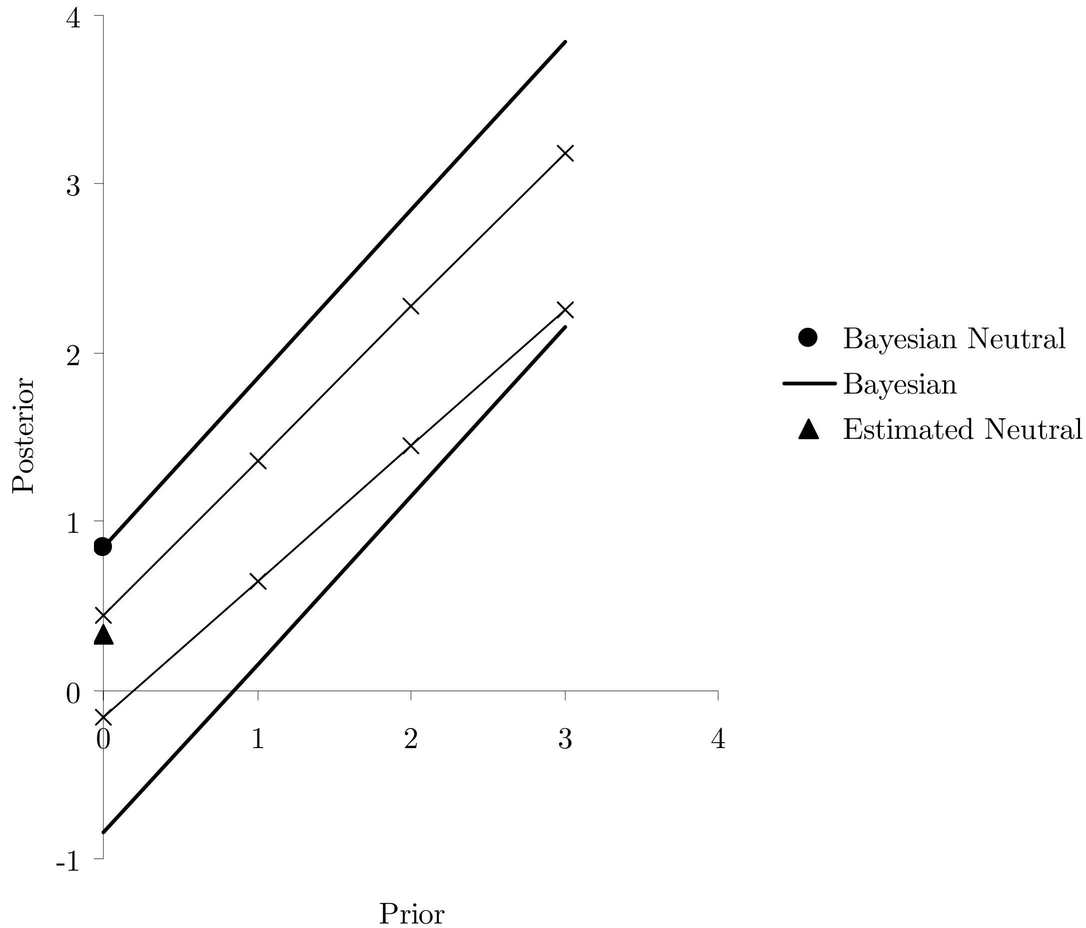

Figure 50: Treatment A Estimated Regression Lines

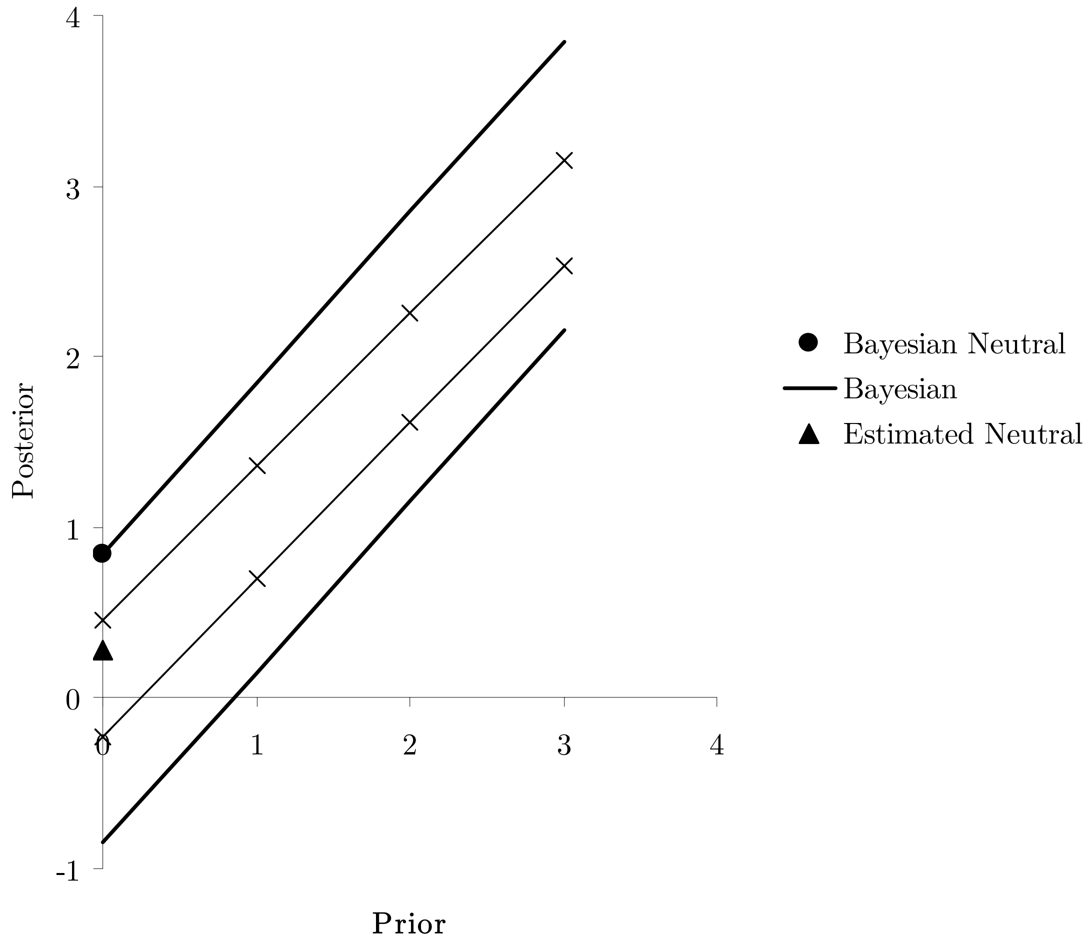

Figure 51: Treatment C Estimated Regression Lines

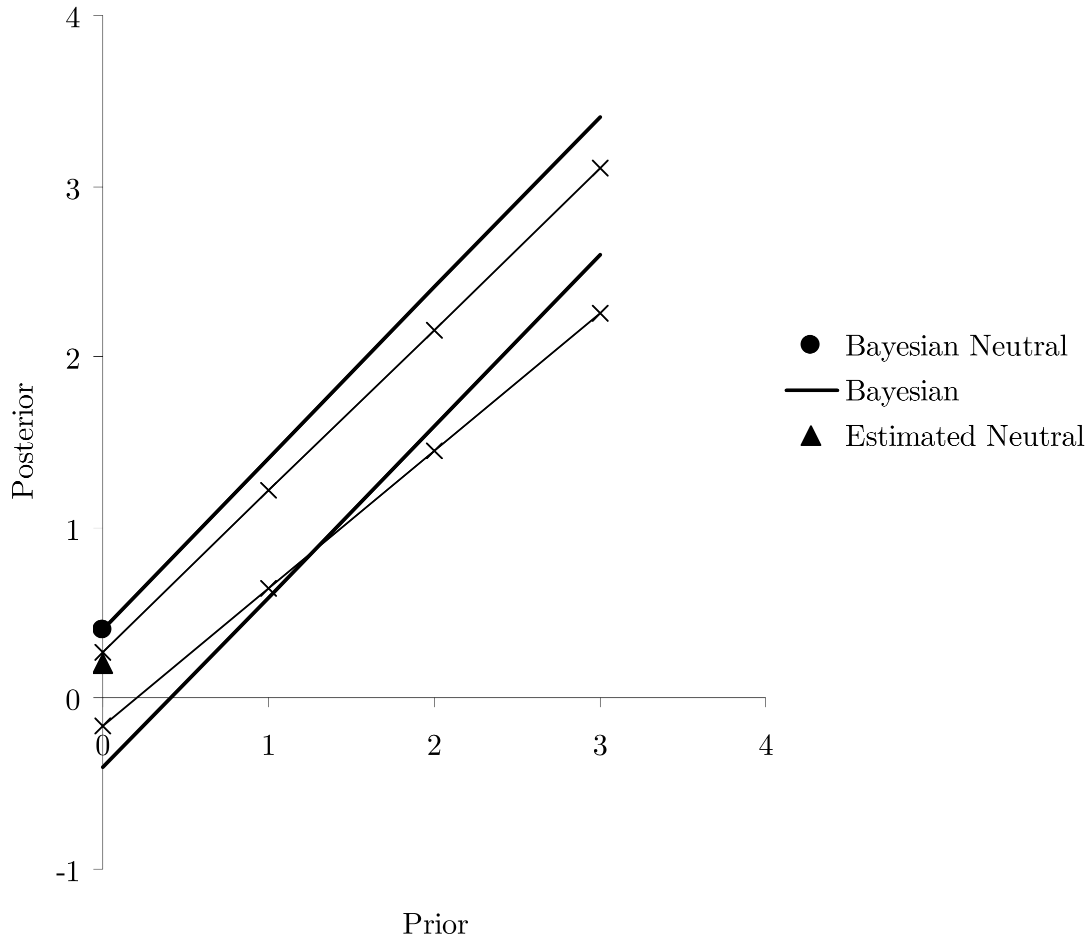

Figure 52: Treatment B Estimated Regression Lines

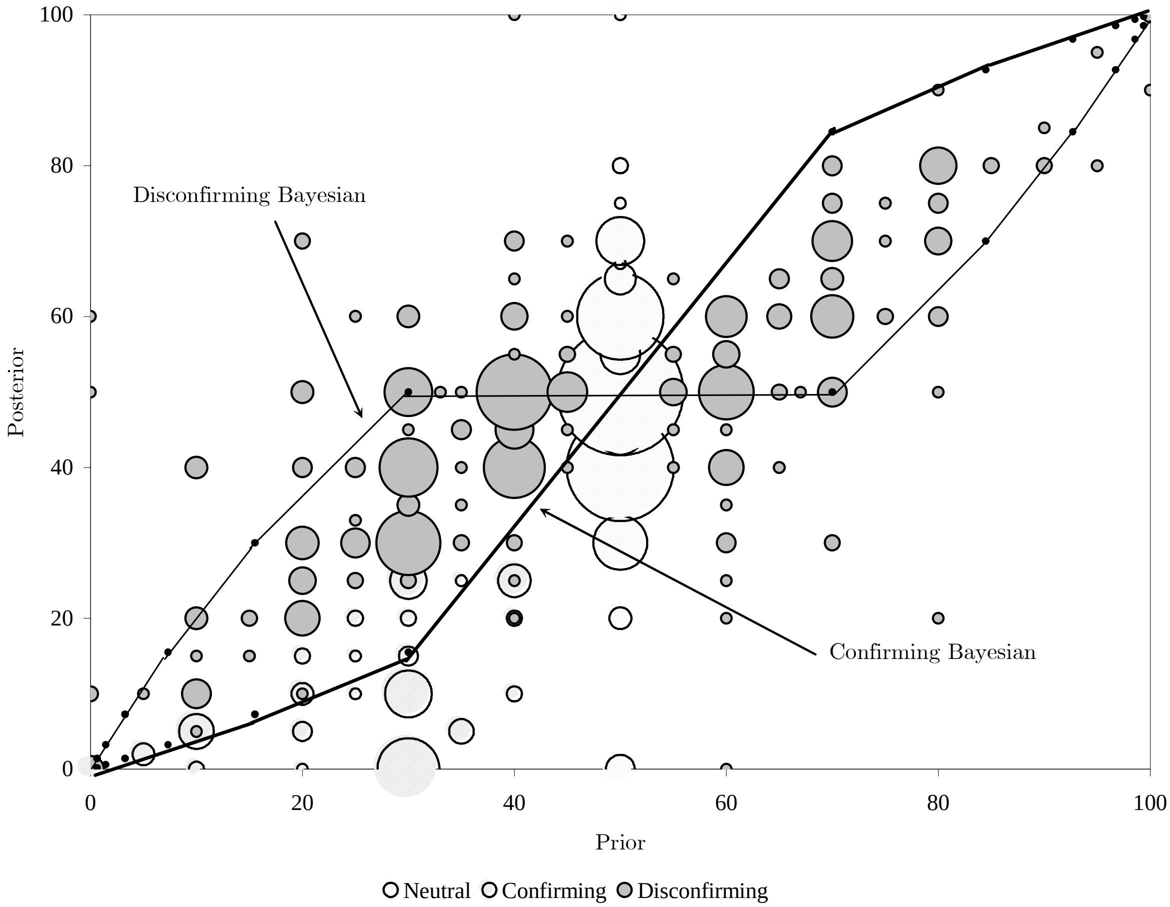

Figure 53: Treatment A Bubble Plot

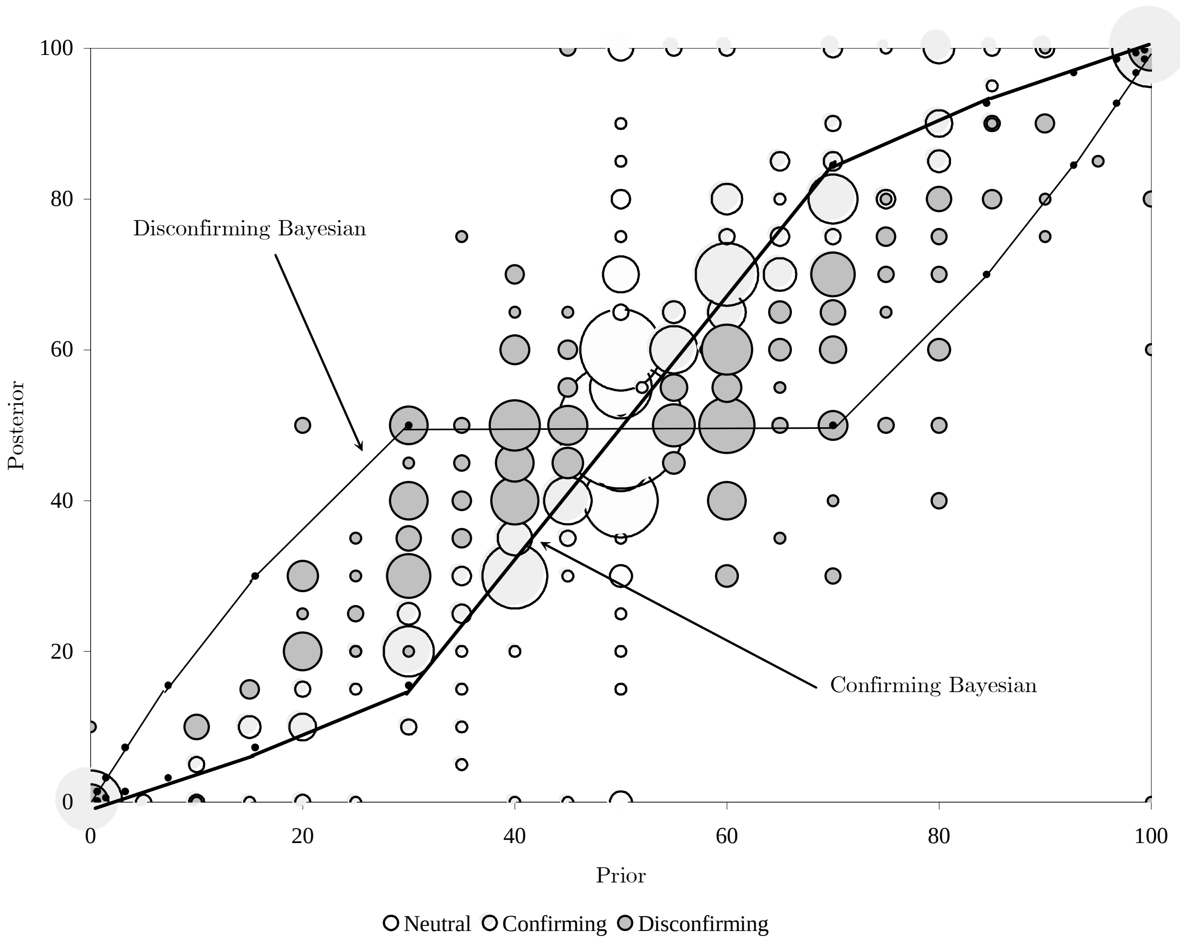

Figure 54: Treatment C Bubble Plot

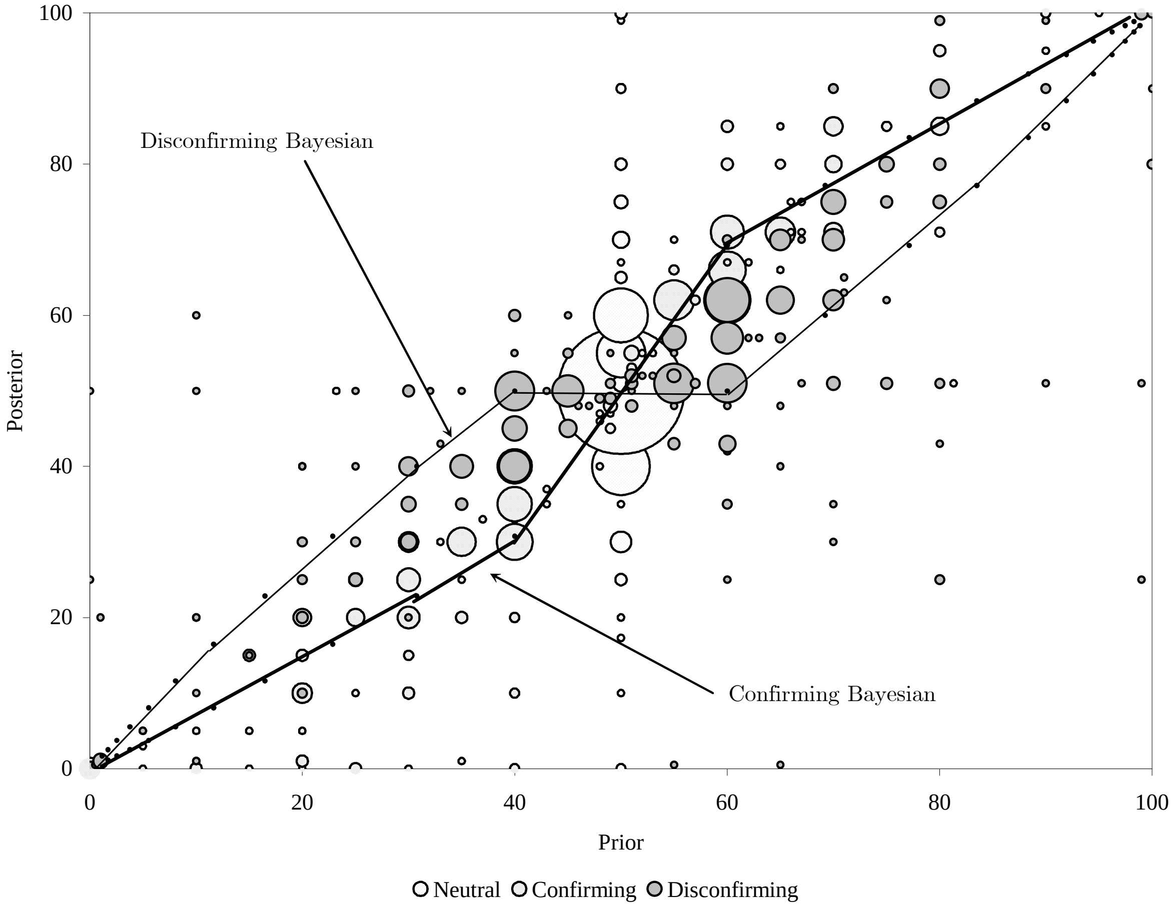

Figure 55: Treatment B Bubble Plot

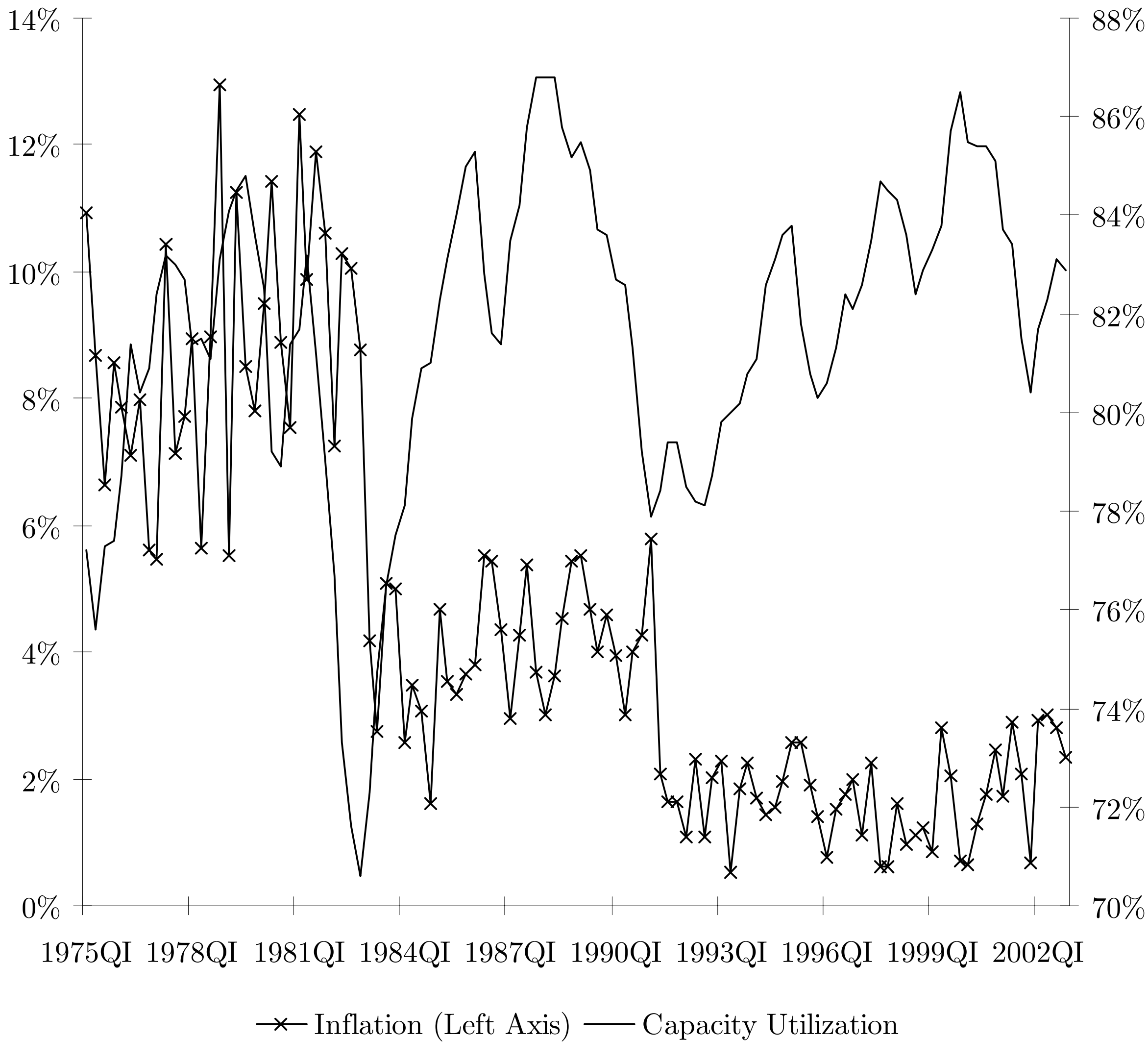

Figure 56: Inflation and utilization for 1975QI-2002QIV

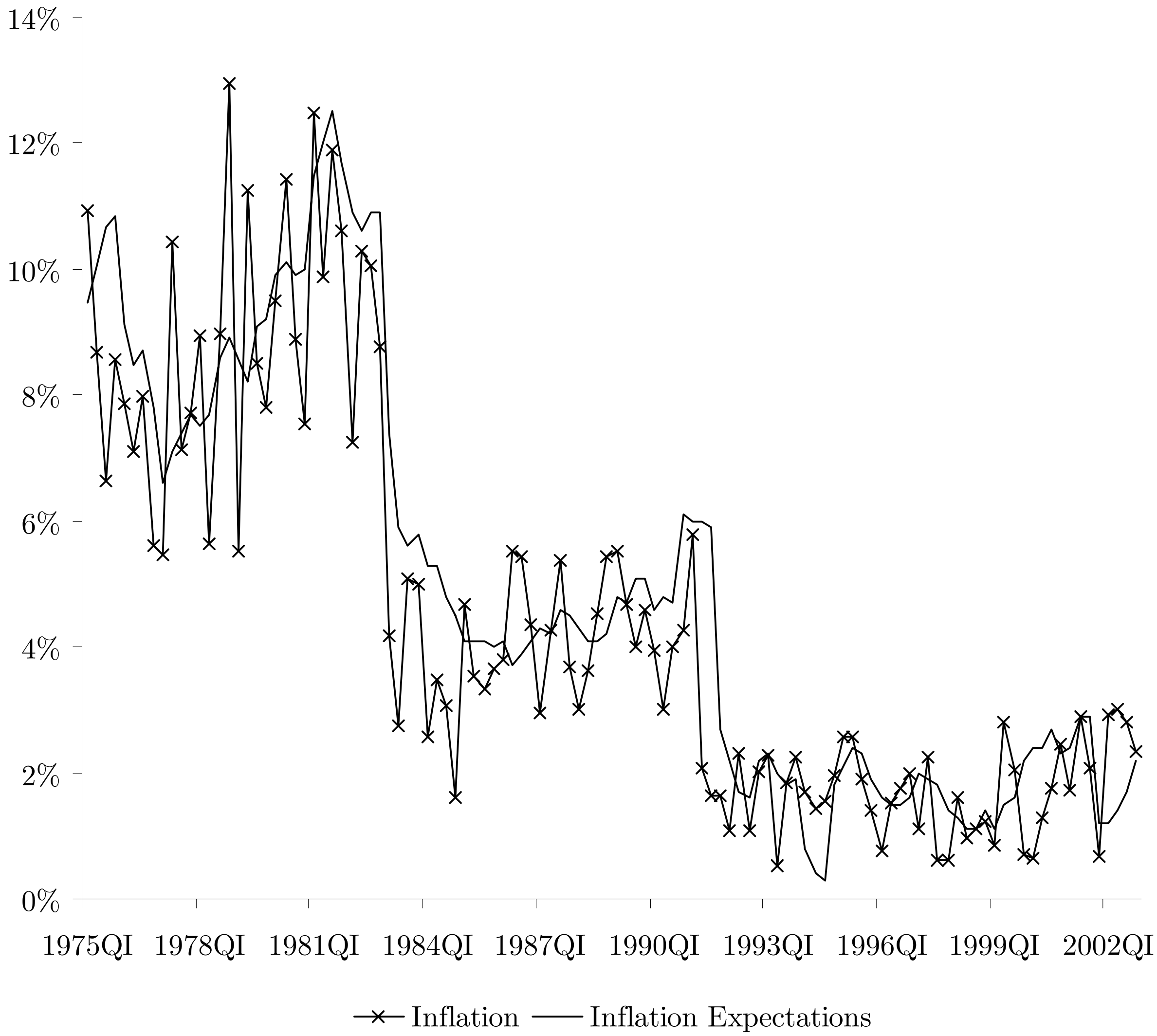

Figure 57: π_t and π_t^e for 1975QI-2002QIV

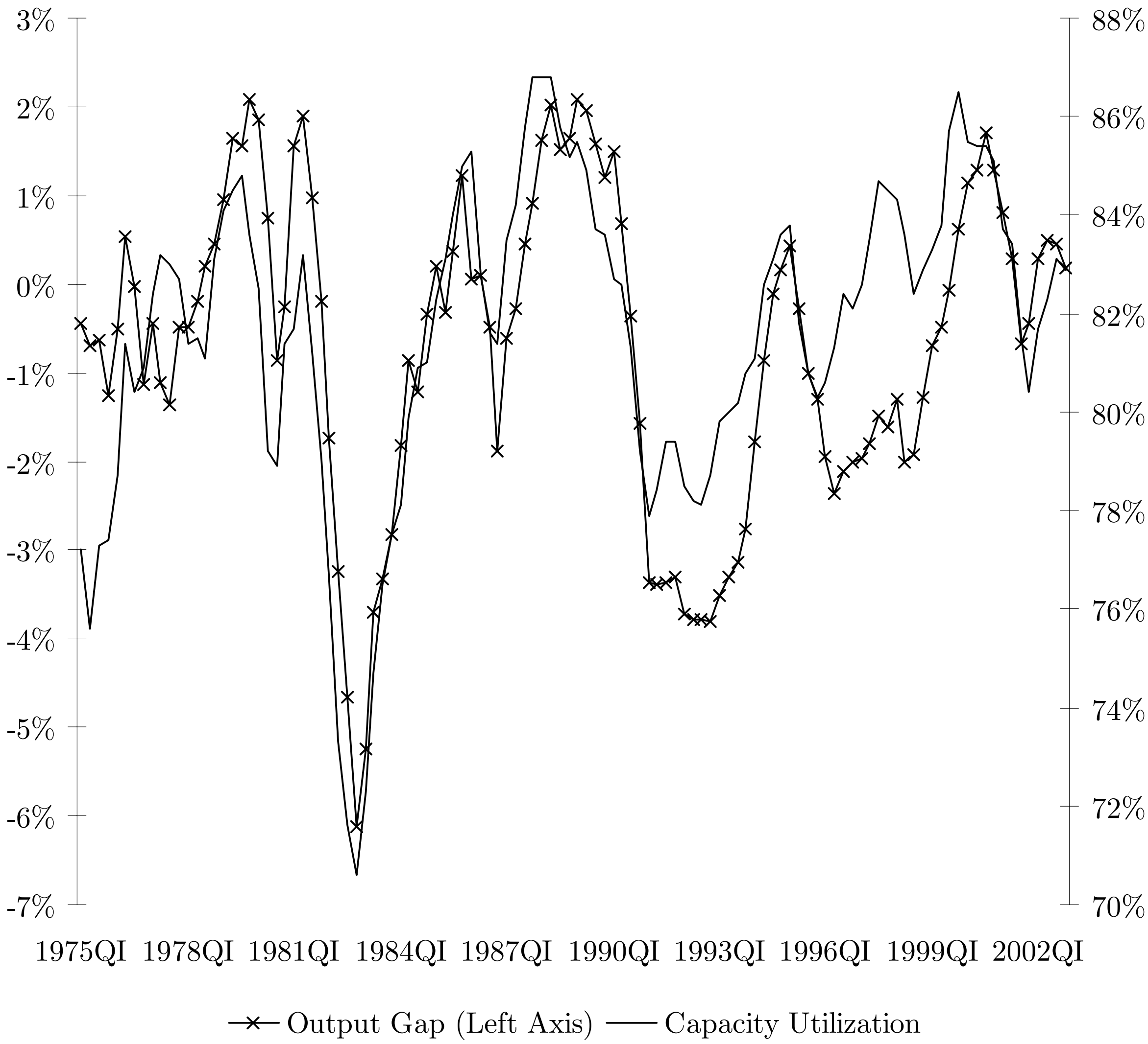

Figure 58: Output Gap and capacity utilization for 1975QI-2002QIV

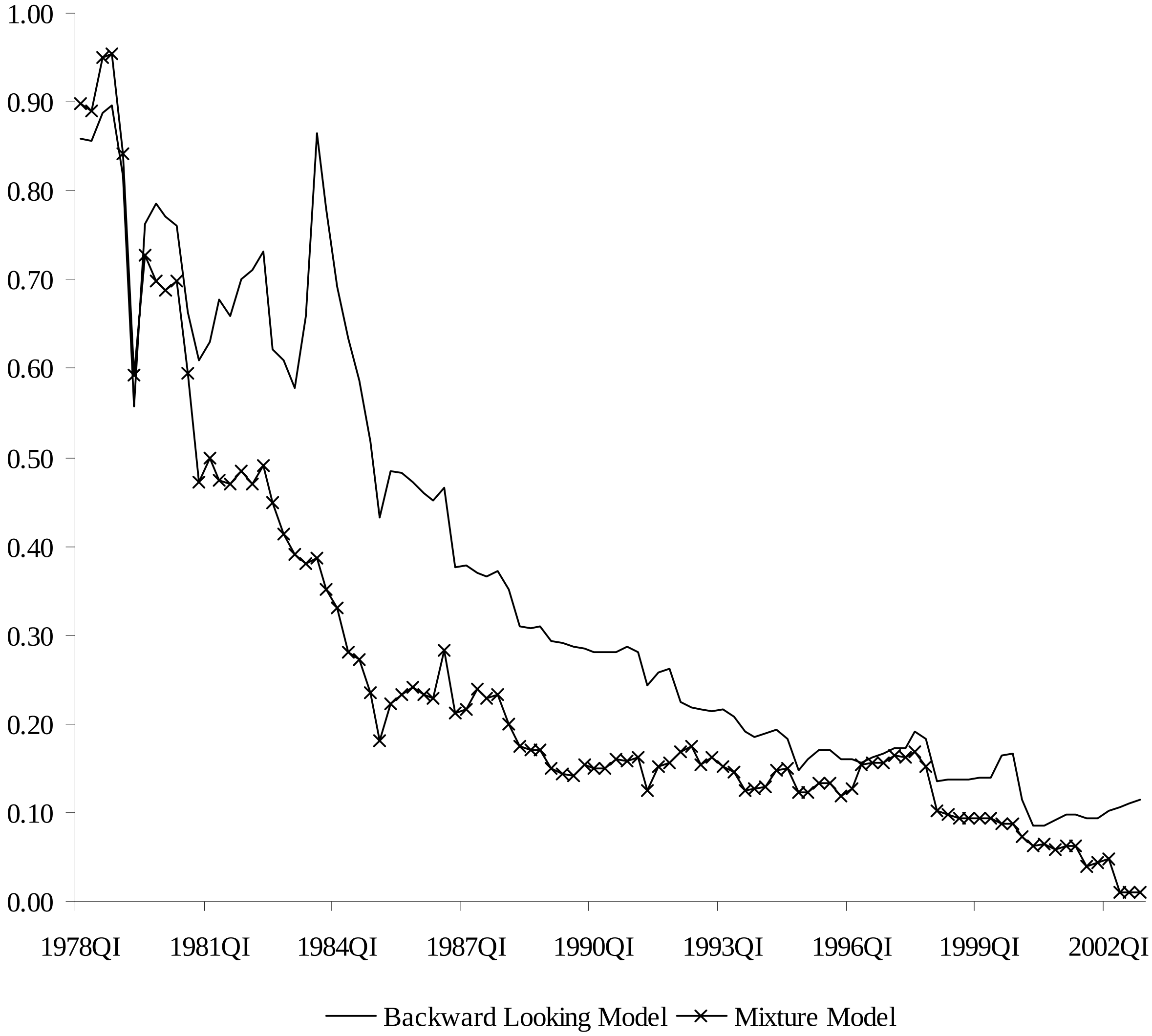

Figure 59: Time varying α_{1t}

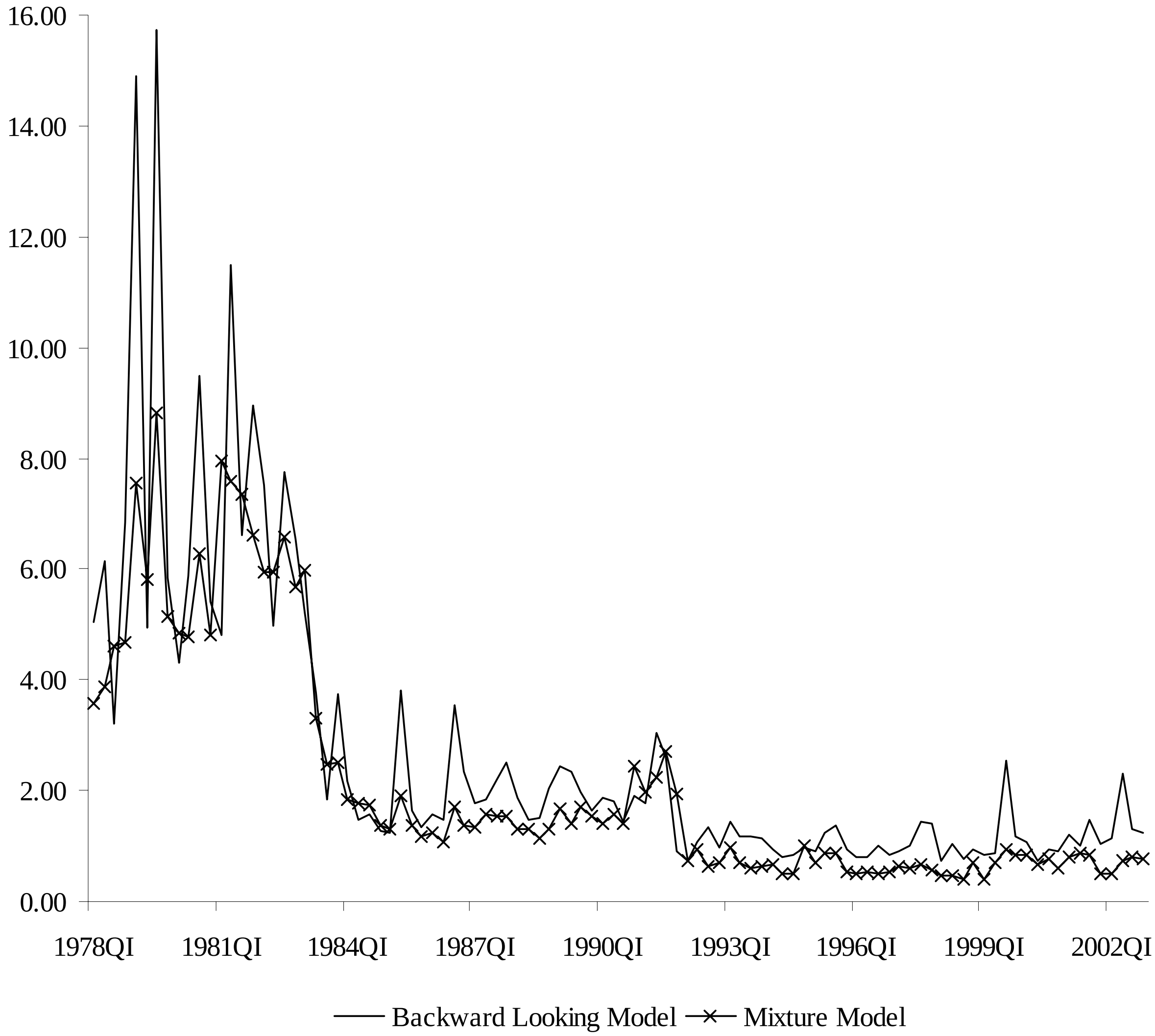

Figure 60: Conditional Variances

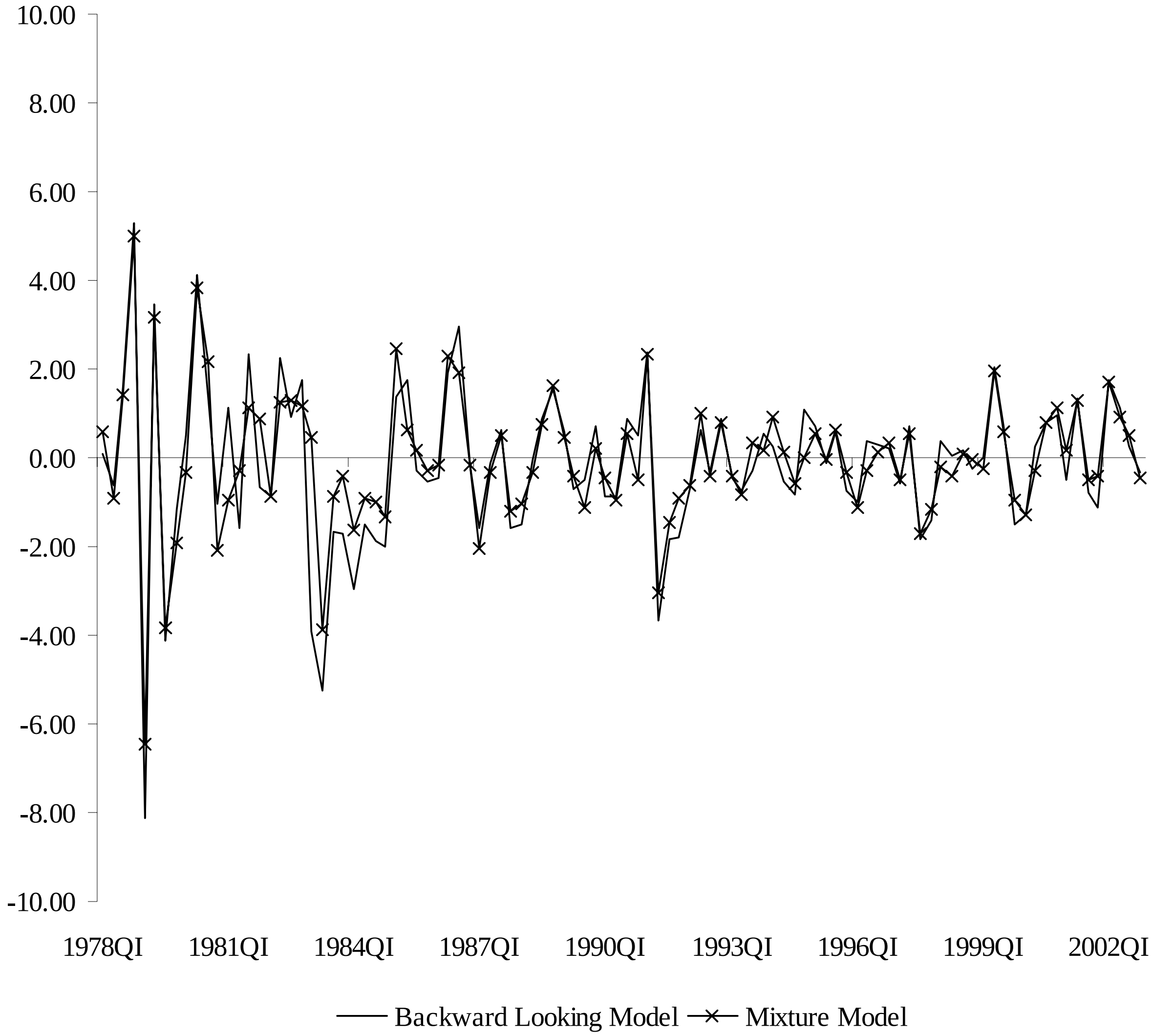

Figure 61: Forecast Errors

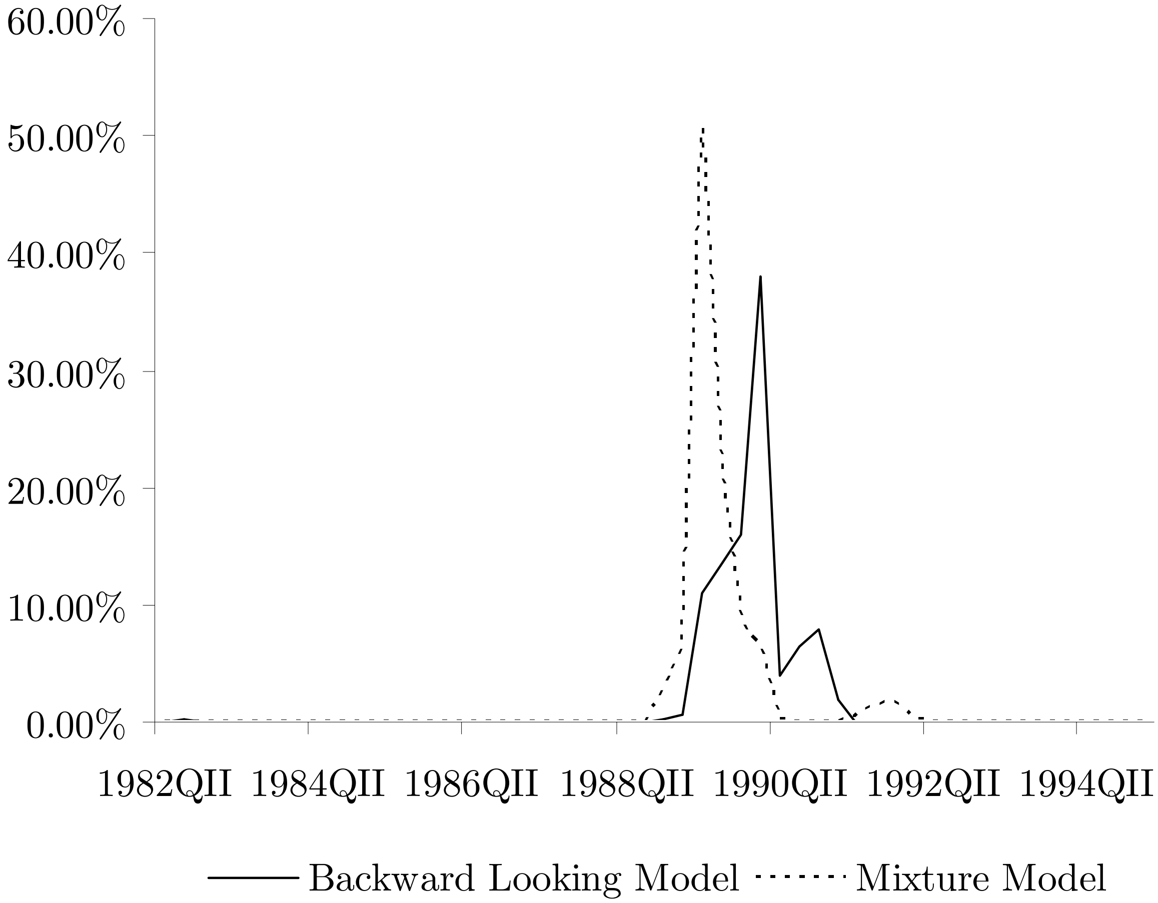

Figure 62: One-Shot Probabilities, No Autocorrelation (1982QII-1995QI)

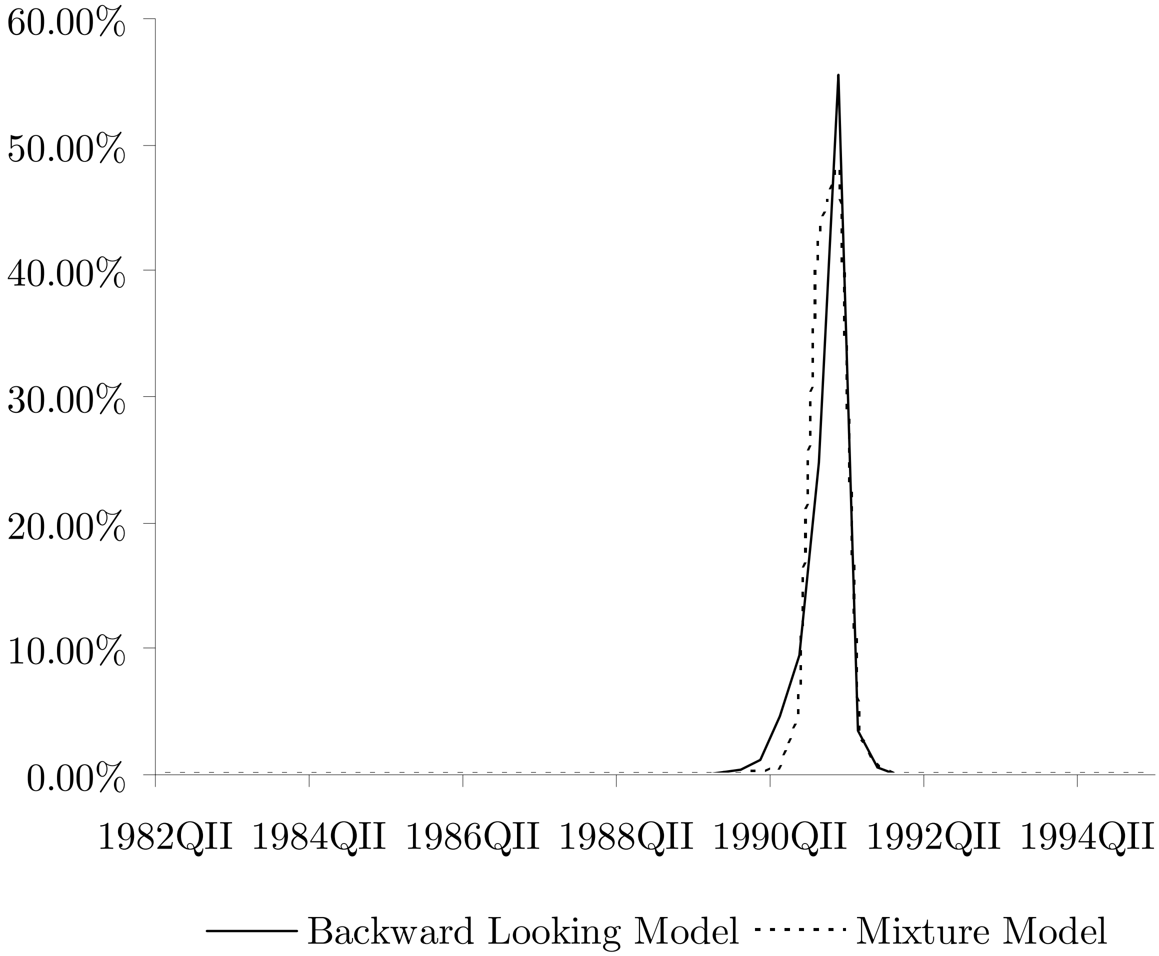

Figure 63: One-Shot Probabilities, AR(1) Errors (1982QII-1995QI)