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A Longitudinal Study of the Impact of Income Dynamics on the Hazard of Divorce

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A LONGITUDINAL STUDY OF THE IMPACT OF INCOME DYNAMICS ON THE HAZARD OF DIVORCE

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During the 1960s, 1970s, and early 1980s, the significant rise in divorce and separation in the United States has caught the attention of scholars, particularly because it coincided with increasing women's labor participation in the workplace. In spite of considerable research on the subject, the research findings on the impact of economic resources on marital dissolution have shown mixed results. One important characteristic of economic resources is the fluctuation in the relative contribution of husbands and wives to household income. Nonetheless, there are no studies in the literature on marital dissolution which have addressed the impact of the income ratio fluctuation on divorce. In this sense, my dissertation is the first attempt to study this phenomenon.

In order to model the instability of the income ratio of husbands and wives, I built an algorithm based on the Theory of Combinations, since linear and curvilinear models (e.g., Ordinal Least Squares Model, Latent Growth Curve Model, and Structural Equation Model) are inadequate to model erratic fluctuations. Once the algorithm was completed, the results were fed into a Logistic Regression Model to test the impact of the income ratio fluctuation on the odds of divorce.

My dissertation encompassed 30 years of data (1968 to 1997), and I found statistically significant results for the late 1970s and the 1980s. Nonetheless, the results were not statistically significant for the early 1970s and the early 1990s. The late 1970s and the 1980s coincided with the worst economic recession in the United States since the Great Depression—with high inflation, high unemployment rate and negative economic growth. It can be argued, therefore, that the instability of the income ratio of husbands and wives becomes a stressor of divorce during economic recession periods. Further research needs to be carried out to test the impact of macroeconomic variables on the impact of income ratio fluctuation on the odds of divorce.

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CHAPTER I

INTRODUCTION

During the 1960s, 1970s and early 1980s, the significant rise in divorce and separation in the United States has caught the attention of scholars. According to Ruggles (1997), only 5% of the marriages in 1867 ended in divorce. On the other hand, about 50% of marriages begun in the late 1960s are expected to end in divorce or separation. In his study of divorce and separation in the United States from 1880 to 1990, Ruggles found that the overall percentage of divorce and separation among white couples (ages 20 to 39) increased 500% from 1880 to 1990. As for the predictors of divorce, Ruggles reported that the rise of nonfarm employment was the most important predictor of divorce and separation from 1880 through 1940. After 1940, however, Ruggles identified the increase in female labor participation as the main contributor to the likelihood of divorce.

Concomitant with this rise in the rate of divorce, women's labor force participation and income have also increased steadily during the 20^{th} century. Oppenheimer (1967) argued that one of the most important demographic trends of the post-war era was the increase in the employment of married women. While there was an increase of 29% in the employment rate of women (age 14 and older) between 1900 and 1940, this rate jumped to 34% in the next 20 years (from 1940 to 1960). The composition of the women's labor participation also changed over this time period. Oppenheimer found that from 1950 to 1960, older women (35 years and older) and married women were entering the labor market at higher rates than younger and single women.

In spite of the increase in the women's labor participation, the 1950s and 1960s showed the prominence of the traditional American family where the husband was the sole breadwinner. According to Oppenheimer (1997) and Nock (2001), this traditional family was used as the benchmark for research on marriage and family. Both authors suggest, nevertheless, that this is indeed an atypical marriage because marital dependency—as opposed to specialization in market and home labor—was the cornerstone of marriages in the 19th and early 20th centuries. Before the advent of the traditional American family, both spouses were dependent on each other to take care of the family farm or small business. Nock argued that these economic dependencies prevented women from exiting their marriages even in the absence of affection. Furthermore, institutions such as religion and government reinforced the economic dependencies of husband and wife.

Recent trends in marriage and divorce signal an alignment with mutually dependent marriages, departing from the traditional American family of the babyboom generation. Nock (2001) coined the term "MEDS" to refer to the equally dependent marriages where both spouses earn between 40% and 59% of the total family income. According to Raley, Mattingly, and Bianchi (2006), by 2001 the majority of the couples (70%) were dual providers, compared to 40% in 1940. By contrast, the percentage of families where the husband was the sole provider decreased from 56% to 25% during the same time period. By 1999, equally dependent marriages (MEDS) represented approximately one-third of dual-income families and slightly more than one-fifth (22%) of all married couples.

According to Nock (2000), the divorce rate has shown a long-term decline starting in 1983, coinciding with the reappearance of the dual-income couple. Furthermore, unmarried childbearing rates also began to decline in the 1980s, and despite the fact that marriage rates have not increased, they are no longer declining.

The concurrence of these two trends—a higher women's labor force participation and an increasing divorce rate in the 1960s, 1970s, and early 1980s—has sparked a heated debate among scholars with opposing views about the impact of women's labor participation on divorce. The research findings are contradictory at best, and shed no light on this particular issue. As for other potential predictors of divorce, several studies have examined the importance of women's increasing income—a by-product of the increasing women's labor participation—on the odds of divorce. Changes or variations in the husband's and wife's income contribution to the household especially merit further research because, as Raley et al.(2006) have found, dual-income families are becoming the norm presently. In other words, according to Raley et al., the new dual-income families show not only an increase in the wife's income respect to her husband's, but also exchanges in the role as the main breadwinner.

There are only a few studies that address the effect of income change on divorce. For example, Weiss and Willis (1997) showed that increases in either spouse's income reduced the odds of divorce. Moore and Waite (1981) found that increases in women's labor income actually increased the odds of divorce. Yeung and Hofferth (1998) showed that income loss increased the likelihood of divorce. On the other hand, Greenstein (1990) found that there was no statistically significant effect of the relative contribution of husband and wife to the family household on divorce. In the same vein, Spitze and South (1985) found no evidence that the relative earnings of husbands and wives have any effect on marital dissolution. Likewise, Tzeng and Mare (1995) showed no impact of changes in either husband's or wife's income on divorce. In short, the findings on the impact of income change on divorce are inconclusive, and in some studies contradictory.

As for the variability of the income ratio throughout time, there are no studies that examine the impact of income instability—defined as erratic fluctuations of the husband's and wife's earnings ratio through time—on the odds of divorce. The significance of the present dissertation is, therefore, the study of fluctuations in the couple's income ratio on the likelihood of divorce because, as stated above, dual-income families are becoming the norm presently.

Research Questions

1. Has there been an increase in the instability of wives' income relative to husbands' income in the United States between 1968 and 1997?
2. Does instability in the ratio of wives' income relative to their husbands' income better predict the likelihood of divorce than stable patterns in the couples' income ratio during the same time period?

3. Are couples with a higher degree of income instability at greater risk of marital dissolution than couples showing a lower degree of income instability during the same time period?

Hypotheses

1. There is increasing fluctuation in the income ratio of husbands and wives in the United States during the last three decades.
2. The couples' income ratio instability constitutes a stressor of family life, and is a better predictor of divorce than stable patterns in the couples' income ratio.
3. Couples showing a higher degree of income instability are at a higher risk of divorce than couples with lower levels of income instability.

CHAPTER II

REVIEW OF THE RELATED LITERATURE

In spite of considerable research on the subject, the research findings on the impact of economic resources on marital instability show mixed results. According to Rogers (2004), the inconclusive and often times opposite findings stem from different research designs, diverse ways of operationalizing key dependent variables, and cross-sectional vs. longitudinal studies. Rogers was able to single out at least four identifiable patterns in the relationship between wives' economic resources and divorce. The first pattern depicts a positive linear relationship between wives' actual income and the probability of divorce. This linear model—with positive slope—is grounded in the Specialization and Trading Model developed by Parsons and Becker (cited in Rogers). This particular model actually constitutes one of the pillars of the theoretical framework in the literature of marital dissolution. I will describe this model in greater detail later in this literature review.

The next model, which Rogers (2004) termed the Equal Dependence Model, shows an inverted U-shaped relationship between wives' economic resources and the probability of divorce. This model is based on the findings of Nock (cited in Rogers). Nock (2001) argues that when the wife's and the husband's contributions to the household are about the same, their mutual obligations are at the lowest point. The underlying idea of this inverted U-shaped pattern is that economic dependency contributes to marital instability. A logical implication that can be drawn from this model (Nock) is that when each spouse contributes between 40% and 59% of the total household income, the commitment and dependency of spouses to each other become marginal.

Heckert, Nowak, and Snyder (1998) found that couples where wives earn between 50% to less than 75% of the household income are significantly more likely to separate than other couples. Nevertheless, Heckert et al. reported that couples where wives earn 75% or more of the family income were less likely to divorce. Locating Heckert et al.'s findings within the framework of the Equal Dependence Model—as Rogers (2004) suggests—may constitute a stretch because the findings support only the right half of the inverted U-shaped curve. In other words, Heckert et al. did not find that husbands earning from 50% to less than 75% of the household income are also significantly more likely to divorce, and that husbands earning 75% or more of the family income are less likely to dissolve their marriages than other households. As becomes clear from the data, the first half of the inverted U-shaped curve is not present in Heckert et al.'s model.

Additionally, there is an important conceptual difference between the Equal Dependence Model and Heckert et al.'s (1998) findings. The underlying idea of the significant impact of the nontraditional couples (where wives earn between 50% and less than 75% of the household income) on the likelihood of divorce—as compared to other couples where the husband is the primary breadwinner—is that this new emerging type of couple is still non-normative and, as such, constitutes a stressor on marital life and a possible cause of divorce. In other words, Heckert et al. did not provide the rationale for their findings based on the Equal Dependence Model, where the likelihood of divorce is the highest when the husband's and wife's income are about the same, and consequently the mutual obligations and commitment are at the lowest point.

A third pattern described by Rogers (2004) draws on the collaborative nature of modern marriages. The model that better fits this pattern is the U-shaped curve. This model is based on the idea that marital stability and satisfaction are higher when both husband and wife are perceived as equal partners, providing an equal share of economic contributions and household work. Several studies found support for this model, which Rogers (2004) named the Role Collaboration Model (see Blumstein & Schwartz, 1983; Blumberg & Coleman, 1989; Coltrane, 1996; Ono, 1998). In particular, Ono found a U-shaped association between wife's and husband's income and divorce, where the probability of divorce was the highest when the wife was contributing too much or too little to the total family income, in other words, when the wife was the breadwinner or when the husband was the breadwinner. This finding was also replicated with a qualitative study (Coltrane) that showed that better economic resources allowed wives to increase their leverage and bargaining power with husbands and obtain better, more equitable, and fulfilling marital arrangements.

The final model described by Rogers (2004) is the Economic Partnership Model. Both the Economic Independence Model and the Economic Partnership Model depict a linear pattern; however, the latter model shows an inverse relationship between wives' economic resources and the probability of divorce. This means that increasing wives' economic contribution to the household actually decreases the likelihood of divorce because wives are in a better position of sharing the economic burden with their husbands and contributing to the formation of marital assets that constitute a barrier against divorce. For instance, Greenstein (1990) found an inverse association between wives' absolute income and the probability of divorce that might be explained by an increase in marital assets such as home ownership and children. Furthermore, Oppenheimer (1997) argued that wives' employment and income contributions to the household have become part of mainstream America during these two past decades. Since wives' economic resources are now normative, a logical corollary is that these increased resources actually lower the risk of divorce in contemporary American society.

From the myriad of possible patterns showing the association between income resources and the probability of divorce, Rogers (2004) made a fairly good attempt to identify the most significant patterns found in the literature on marital dissolution. The four models depicting these prevalent patterns—the Economic Independence Model, the Equal Dependence Model, the Role Collaboration Model, and the Economic Partnership Model—are grounded in two conceptual models of marital dissolution that constitute the pillars that provide the rationale and theoretical framework to the models described above. These two models are the Specialization and Trading Model (Becker, 1974; Parsons, 1949) and the Collaborative Model developed by Oppenheimer (1997).

In the next section of this literature review, I will describe these conceptual models in greater detail and discuss the relevance of these conceptual models to the research question. The underlying idea of analyzing and contrasting the different models and research findings within the framework provided by the research question is to identify new areas of research in the literature on marital instability and opportunities to build on past research. In this sense, my research interest is to identify the impact of income instability on marital dissolution. Finally, I will develop a conceptual model in the last part of the literature review. This model will be built on past research on marital dissolution and will attempt to provide a rationale for the findings that I expect to obtain from my dissertation.

The Specialization and Trading Model (Becker, Landes, & Michael, 1977) is an extension of Microeconomic Theory. The cornerstone of this theory is the maximization of the utility function of individuals. According to Economic Theory, human beings are regarded as rational beings who are prone to make decisions that maximize their individual utility functions in the different spheres of their lives. Marriage is one area where the individual utility function, as well as the couple's function, is subject to maximization. According to Becker et al., people will marry if their expected utility from marriage exceeds the utility from remaining single.

A logical corollary of the Specialization and Trading Model is that couples will decide to divorce if the actual utility derived from marriage is lower than the utility they expected to obtain from marriage. This expected utility is maximized when husbands and wives specialize in what they do best: husbands in market work and wives in housework. By contrast, when either the wife or the husband decides to assume an economic role where she or he does not have a comparative advantage, the net result is a decrease in the couple's utility function. This decrease in the utility function of the couple may increase their likelihood of divorce. According to the Specialization and Trading Model, in short, the increasing participation of wives in the labor market and the subsequent increase of their labor income relative to their husbands' income have a statistically positive impact on the likelihood of marital dissolution.

On the other hand, Oppenheimer (1994, 1997) argues that wives' labor market participation actually buffers marriage against the economic instability of modern times. Due to this buffering mechanism, the wives' participation in the labor market has become increasingly normative in the past decades. Oppenheimer's rationale is that traditional couples where the husband is the only breadwinner are becoming increasingly vulnerable because job instability, work injuries, and illness could prevent the husband from performing his traditional duties as the economic provider of the family. On the contrary, having two potential breadwinners could increase the options available to couples in order to face adversity. In this sense, a partnership model—where both husband and wife participate in the labor market—emerges as a survival mechanism in present times.

This survival mechanism replaced prior, albeit successful, family structures from the past. In the late nineteenth and early twentieth centuries, for instance, children actively participated in the labor market to supplement the father's income (Oppenheimer, 1994). Children's labor force participation was also accompanied by a higher rate of fertility than has occurred more recently.

This family arrangement, nevertheless, became increasingly inefficient because children who started to work early in their lives were deprived of schooling, which had a major impact on the stream of family income in the future. Furthermore, the passage of laws forbidding child work in industrial societies made this family organization outdated. According to Oppenheimer (1994), another reason why women replaced children in the labor market was the increasing need for skilled labor in technology-oriented countries.

It is important to note that Oppenheimer (1994, 1997) extended her model to explain not only marital dissolution, but also other demographic trends such as fertility, delayed marriage, and nonmarriage. Based on a longitudinal study that covered 26 years (1963 to 1989) of the aggregated weekly income ratio of women and men (instead of husbands and wives), Oppenheimer argued that increasing women's earnings does not provide a satisfactory explanation for the diminishing rate of fertility and increasing rates of divorce, delayed marriage, and nonmarriage. Despite the fact that the income ratio (women's average weekly income divided by men's average weekly income) showed a steady increase from 1963 to 1989, the denominator of the ratio accounts for most of this increase. In other words, the persistent decrease in men's income, due to precarious job opportunities especially for young males with few years of education, is actually driving the income ratio upwards. In summary, based on Oppenheimer's longitudinal analysis, it is problematic to make the argument that the increase in women's income resources in the last decades has resulted in an increase in the women's and men's income ratio, and through this ratio, in an increase in the odds of divorce.

Rogers (2004) located Oppenheimer's (1994, 1997) Collaborative Model as the conceptual basis for the Economic Partnership Model that predicts an inverse relationship between the wives' actual income and the probability of divorce. While it makes conceptual sense to explain this negative relationship with the basic tenets of the Collaborative Model, it makes better sense to locate the Collaborative Model as the theoretical basis for the Role Collaboration Model (U-shaped curve). The key concept for making this distinction is flexibility. The core feature that defines the Collaborative Model as a survival mechanism is the flexibility that both husband and wife enjoy in adopting the breadwinner's role depending on the external threats and economic challenges that the family may face. On the other hand, a corollary derived from the Economic Partnership Model is that an increase in wives' income will translate into a smaller probability of divorce. This reasoning does not hold true for an increase in the husbands' economic resources. Therefore, the pattern that depicts a negative relationship between wives' actual income and the probability of divorce has the undesirable effect of undermining the inner flexibility that lies at the heart of the Collaborative Model.

Despite the fact that the two marital dissolution models described above (the Specialization and Trading Model, and the Collaborative Model) are at odds with each other, Ono (1998) was able to integrate these apparently contradictory models into a single one. This model is U-shaped and sheds light on the complexities inherent in the couples' income dynamics. Ono argued that the effects of both models prevail or offset each other depending on the level of the wife's income. For instance, when the wife's earnings are in a low range that prevents her from living independently, an increase in her earnings actually may reduce the likelihood of divorce. At this level, the income effect (derived from the Collaborative Model) will prevail. On the other hand, once the wife's earnings exceed the level where she can live independently, the independence effect (based on the Specialization and Trading Model) will take over, actually raising the likelihood of divorce. The overall effect is a U-shaped curve that integrates these two conceptual models.

What is the relevance of these research findings and marital dissolution models to the research question? There are two fundamental concepts that emerge from a careful examination of the literature on income dynamics and marital dissolution: the impact of wives' economic resources on the likelihood of divorce, and the different patterns that depict this association. The increasing participation of women in the labor market is a well documented phenomenon that coincided with a substantial increase in the divorce rate in the past decades. The simultaneous presence of these two trends has fueled a heated academic debate with inconclusive results as to whether or not women's increased labor participation and concomitant higher income are good predictors of the likelihood of divorce. Different patterns describing this relationship and its complexities have been found, and several models have been built—such as the four models introduced by Rogers (2004)—to depict these patterns. Nevertheless, there are no studies which directly address the impact of income instability on the likelihood of divorce. Instability, defined as erratic fluctuations with no identifiable pattern, is conceptually different from patterns, tendencies or data trends.

Most studies concentrate on identifying patterns in the data in order to built models for hypothesis testing and prediction. On the other hand, erratic fluctuations are usually overlooked in ordinary least squares models. A logical conclusion of the previous analysis is that linear or curvilinear models (either with observable or latent constructs) are adequate tools to model patterns; however, they are inappropriate to depict instability. In short, another kind of model should be used or developed to adequately model instability.

As for linear and curvilinear patterns, the Logistic Regression Model and the Proportional Hazards Model are the methodology of choice in the literature of marital dissolution for modeling linear trends, such as the impact of increasing women's income on the odds of divorce. For instance, Ono (1998), using a Logistic Regression Model, found that wife's earnings have a U-shaped relationship with the odds of divorce. Using the same technique, Rogers (2004) found that wives' income showed an inverted U-shaped curve with the odds of divorce. Heckert et al. (1998) showed that the relative contribution of husbands and wives to the household income is a predictor of divorce, although this association is nonlinear. Heckert et al. also used a Logistic Regression Model for their study.

The Proportional Hazards Model is also a popular model in the literature of marital dissolution. Teachman (1982) argued that the Proportional Hazards

Model in general and the Cox Model in particular are better suited for the analysis of family formation and dissolution than Ordinary Least Squares Regression. This is because marital dissolution, as other precipitating events in life, is a process rather than a structure. Therefore, Teachman recommended dynamic models, such as the Proportional Hazards Model, as the appropriate data-analytic strategy for modeling marital dissolution. Furthermore, Teachman and Polonko (1984) argued that the Proportional Hazards Model is the ideal fit to model marital dissolution because it can handle both truncated events (censored cases) and account for the fact that the pace at which events occur may not be constant over time. For example, Teachman (1982) found that marital dissolution occurs at a more rapid pace in the earlier years of marriage than in the later years of marriage. Interestingly, Teachman also argued that "husband and wife incomes and their ratios may change with time, and such changes can be argued to have an impact on marital dissolution" (p.1049).

In addition to these widely used models, the Structural Equation Model and the Latent Growth Curve Model were also used to assess the impact of economic resources on marital dissolution (e.g., Rogers & DeBoer, 2001; Kurdek, 2002; Baer, 2002). To model role configurations and pathways in the life course of families, The Latent Path Analysis was the model of choice (see Macmillan & Copher, 2005).

Conceptual Model

My research interest is to model the impact of income instability on the likelihood of divorce because I hypothesize that income instability has not been assimilated into the mainstream United States as a norm. I also hypothesize that income instability constitutes a stressor of family life and a possible predictor of marital dissolution because erratic income fluctuations, as opposed to linear and more stable trends, are more difficult to become normative in modern American society. Nock (2001) argued that equally dependent couples are at higher risk of divorce than couples where either the husband or the wife is the main breadwinner. In terms of income fluctuation, this means that couples with income ratio variations ranging from 40% to 59% are more prone to marital dissolution. Nock further contends that MEDS (marriages of equally dependent spouses) will become the family structure of the future. Along the same line of reasoning, I argue that dual income families are currently the most pervasive type of family in the United States—they constituted 70% of the total number of families in 2001––and that income ratio fluctuation has a statistically significant effect on the likelihood on divorce throughout the whole range of the income ratio (from 0% to 100%). This income ratio actually captures all possible combinations of dual income couples, including MEDS. My hypothesis is that income ratio fluctuation affects the likelihood of divorce of all dual income couples, including MEDS, because I argue that income fluctuation is non-normative and stressful throughout the entire range of the income ratio of husbands and wives.

In order to capture income instability, both the husband's and the wife's income should be taken into account because both incomes can show erratic fluctuations. This means that the model that I want to use should include the income ratio of husbands and wives as the independent variable of interest.

Furthermore, this model should depict instability instead of income ratio patterns. The modeling of trends, however, is a useful piece of my dissertation because I want to assess whether various patterns of income stability or erratic fluctuations are the best predictors of divorce. As will become evident, a key component of my dissertation is the development of a model that identifies couples with erratic income ratios. In the methodology chapter of this dissertation, I will discuss in greater detail the development of this model and the operationalization of income instability.

After designing and implementing the model, I expect to find more income ratio fluctuation in recent years as compared to the early 1970s and 1980s. I also expect to find a greater impact of erratic income fluctuations on the likelihood of divorce compared to the impact of linear or curvilinear income patterns in the United States from 1968 to 1997. Finally, I expect that couples showing a higher degree of income instability to be at a higher risk of divorce than couples with lower levels of income instability during the same time period.

CHAPTER III

METHODOLOGY

Characteristics of the Database

The Panel Study of Income Dynamics (PSID) is a longitudinal dataset of a representative sample of U.S. men, women, and children and the households in which they reside. This study has been conducted by the Survey Research Center at the University of Michigan since 1968 and has an ongoing nature; the last data collection occurred in 2003 including economic, demographic, and sociological information on more than 65,000 individuals. The sample size has grown from 4,800 families in 1968 to more than 8,000 families in 2003, due to family splitoffs and continuous replacement of individuals who die during the length of the study (http://simba.isr.umich.edu/VS/s.aspx).

This considerable increase in the sample size allowed the PSID to remain nationally representative, unbiased, and self-replacing sample of families in the United States throughout the 35 years that data have been collected (http://simba.isr.umich.edu/VS/s.aspx). According to Heckert et al. (1998), this is because the PSID traced all participants who left their homes from the original 1968 sample to start households on their own or join other households. Actually, the original PSID sample combines two independent samples: a cross-sectional, national sample of the civilian noninstitutional population of the U.S. gathered by the Survey Research Center (SRC) and a sample from the survey of Economic Opportunity (SEO) conducted by the Bureau of the Census for the Office of Economic Opportunity. This latter sample was intended to include about 2,000 low-income families with heads under 60 years old (http://simba.isr.umich.edu/VS/s.aspx).

Both samples are probability samples, but their combination nevertheless is a sample with unequal selection probabilities, which therefore requires the implementation of a complex weighting scheme to account for this unequal selection probability. Additionally, the sample weights attempt to compensate for differential attrition and differential nonresponse in 1968 and subsequent waves. Weighting is actually a procedure for adjusting the distribution of units in the sample so that the frequency attached to each unit reflects the frequency in the total population, rather than in the sample. Therefore, in the present analysis it is essential to use weighted data (family-level weights), since unweighted data are only representative of the sample of heads of households who responded the annual PSID questionnaire (http://simba.isr.umich.edu/VS/s.aspx).

Heeringa and Connor (1999) reported that the net effect of the offsetting processes of attrition and continuous replacement of individuals who left the study has increased the PSID sample throughout time. As a result, starting with the 1997 wave of data collection, the PSID Board decided to reduce by one-third the original number of 1968 families eligible for continuous longitudinal collection, add the supplemental sample of post-1968 immigrant families (to maintain national representativeness of immigrant families), and gather information every two years instead of annually.

Attrition and Missing Values

This increase in the sample size has created unique challenges for researchers working with the PSID dataset. For example, attrition has become an important concern because heads of households have died, gotten separated from their wives, and in some instances, created new households over this extended time period. Sons have also left the nuclear family and created households on their own. According to Fitzgerald, Gottschalk, and Moffitt (1998), however, there is no evidence that attrition has undermined the representativeness of the PSID Dataset. Furthermore, Lillard and Panis (1998) found that in spite of the presence of significant selectivity in attrition behavior, the biases that are introduced in dynamic behavioral models built with the PSID dataset are generally mild. In terms of the missing data, the PSID assigns a missing code (i.e., nine) or an imputed value is assigned in lieu of a missing data code (http://simba.isr.umich.edu/VS/s.aspx). For the purposes of the present dissertation, I did not impute any data but made forward or backwards assignments of control variables to the years where these variables were not gathered. These assignments were carried out only for fixed control variables and will be thoroughly explained in the control variables' section.

From a technical standpoint, the huge number of variables included in the dataset constituted an unexpected complication, especially for a longitudinal study. The 1968 Family File contains, for instance, 442 variables. By contrast, the 2001 Family File contains 3,400 variables. The downside of this considerable increase in variables over time is that it becomes difficult to track down variables, especially the ones included as independent variables in a longitudinal study, because they are not reported in every year of the study. Additionally, some key independent variables have changed their name throughout time, complicating things even further. On the other hand, the PSID dataset is well suited for modeling dynamic processes, such as income instability. The PSID dataset offers 35 years worth of detailed economic data, making it possible to study income variability throughout time. By contrast, smaller datasets or cross-sectional studies are unable to capture income instability since this is in essence a dynamic process.

Data Management and Merging Process

Since the dataset includes more than 8,000 families and more than 3,400 variables, a rather tedious and long merging process is required to build the dataset. This dataset consists of separate, single-year files with family-level data collected in each year and one cross-year individual file with individual-level data collected from 1968 to 2003 (http://simba.isr.umich.edu/VS/s.aspx). This cross-year individual file is actually the anchor file, containing information on every individual ever in the study. On the other hand, the family files contain one record on each family interviewed in every year of the study.

The idea behind the merging process consists of consecutively merging each family file (for every year) to the anchor file. This merging approach (one-to-many in SPSS) links the information-rich family files to every individual included in the study. The PSID interviewed only the head of household to gather the income-related information for the whole family. For this reason, the files corresponding to the wife and children were trimmed away to reduce the size of the merged file. It would have been very useful to obtain income data reported directly from the wife to cross-check the information provided by the head of household; however, all income data collected by the PSID came only from the head of household.

In spite of the trimming described above, the resulting merged file was 1.22 GB. Because of this big size and for conceptual reasons, cross-year/family files (covering five years each) were created to cover the entire period of the study. For the purposes of this dissertation, therefore, data from 1968 to 1997 were used to create six five-year cross-year/family files. The cross-year/ family file corresponding to 1998 to 2003 was not created because, starting in 1997, the PSID collected data every second year. In other words, this cross-year/family file would not be comparable—for the purposes of a longitudinal analysis—with the previous cross-year/family files because it would include data for every second year starting in 1999. These cross-year/family files were built using the same merging procedure utilized to build the merged file for the entire time period (1968 to 1997). Specifically, the cross-year/family files that were built were 1968 to1972; 1973 to 1977; 1978 to 1982; 1983 to 1987; 1988 to 1992; and 1993 to 1997.

The underlying idea behind selecting a five-year period is that it is a reasonable time to model income instability, my primary variable of interest. Several studies (see Kurdek, 2002; Baer, 2002; Cox, Paley, Burchinal & Payne, 1999) used a similar length of time to model dynamic processes. For example, Kurdek (2002) applied latent variable curve analysis (initial level and rate of change) to assess the impact of individual difference variables for the first four years of marriage on the timing and physical separation of individuals. Furthermore, Duncan, Duncan, Stricker, Li, and Alpert (1999) argued that two observations are insufficient to model change because two data points perfectly define the initial level (y-intercept) and growth rate (slope) of a linear latent growth curve. In this sense, three or more observations are required to adequately model dynamic processes.

The structure of the five-year cross-year/ family files is, nevertheless, more complex than initially described. In other words, these files are not independent of each other; they are linked by the divorce history variable that was created to single out the heads of household who are in their first marriage only. From a theoretical standpoint (see Nock, 2001; Rogers & DeBoer, 2001), individuals in their second, third or subsequent marriages are at a greater risk of divorce than individuals in their first marriage. For this reason, it was fundamental to devise a mechanism to keep the heads of household who were married only once in each five-year cross-year/family file and exclude remarriages. The PSID website contains a file that includes cumulative divorce data starting in 1985 up to 2003. This marital history file started in the 1985 wave by asking complete retrospective marital history information of the heads and wives included in the study. In all subsequent waves, this marital information was updated to include changes in the marital status of the participants (http://simba.isr.umich.edu/VS/s.aspx).

After a careful examination of the 1985-2003 Marriage History File, however, the cumulative nature of the divorce variable was not found to be suitable for the merged structure of the five-year cross-year/family files. Many cases would be lost with this variable. For example, a head of household who divorced in 1985 would be assigned a code for “divorced” and, since this variable is a cumulative variable, this particular case would be excluded from the previous five-year periods (e.g., 1968-1972, 1973-1977, and 1978-1982) where the head of household could have been in his first marriage. It is true, nonetheless, that this file contains additional marital history variables that allow identifying with more precision the year in which a person divorces or whether the person is in his first marriage or not, but with six independent five-year cross-year/family files, tracking the divorce history for every head of household becomes cumbersome.

For this reason, a divorce variable was created to identify heads of household in their first marriage. Once this variable was created for the first period (1968-1972), it was merged to the following periods. Each time this variable was merged to the next five-year cross-year/family file, it was updated and subsequently merged to the next five-year cross-year/family file. The criterion for identifying heads of household in their first marriage was simple: once they become divorced or widowed, they were assigned a code for “divorced.” Since this divorce history variable was carried over to the next five-year periods, this variable was used to exclude the divorced heads of household in the subsequent periods yet keep them in previous periods where the heads of household were single or in their first marriage.

The complexity of creating this divorce variable was further compounded by the structure of the family files. These files contain information on the head of household only, and when the family files are merged into the individual file (that contains basic information of all the members of the household), the children "inherit" the detailed information of their father that is contained in the family files. Part of this inheritance is the divorce history of the father. Once these children leave their parents and start their own families, they would become heads of household. If their parents were previously divorced, these new heads of household would also be coded as "divorced." This marital status would prevent them from participating in this dissertation. In order to deal with this complication, the divorce variable was created based on the individual's relationship to head as well as his marital status. If, for example, an individual has a "divorced" marital status but is coded as a child, his previous divorce history would be erased, so that when he becomes a head of household, he would have no previous divorce history. In sum, this divorce variable was built as a conditional variable based on marital status and on relationship to household head. A second component of the formula was written to actually create the new divorce history of the children once they become heads of household.

Finally, a moderate amount of data integrity was carried out to test the reliability of the merging process. Random cases were identified and followed through time to determine whether the merging process was done correctly or not. In short, several cases and time invariant variables (such as gender and race) were selected to check if the same individual maintains the same gender and race throughout time. This analysis indicated that the merging process was done correctly.

Control Variables

Several studies on the odds of divorce consistently include the same covariates and dependencies in their analysis such as education, age, religious affiliation, age at first marriage, number of years married, and hours worked. Each of these has been found to influence the likelihood of divorce or separation (see Nock, 2001; Rogers & DeBoer, 2001; South, 2001; Ono, 1998). For instance, South and Spitze (1986) found that variables such as race, wife's labor force participation, and husband's employment seem to affect the probability of marital dissolution, regardless of the stage in the marital life course. In his analysis of equally dependent marriages, Nock (2001) included well-known risk factors for divorce such as cohabitation, education, age at first marriage, presence of preschool children, total number of children in the household, hours worked, race, and earnings. Ono (1998) used age of youngest child, presence of children, race, and age at first marriage as control variables in her study of the impact of the relative income contributions of husband and wife on the odds of divorce. Similarly, Rogers (2004) used husband's and wife's actual income, years married, number of children, education, gender, race, and marital happiness. In their study on dual-income couples, Raley et al. (2006) included men's labor supply, race, wife's age, wife's education, number of children, and age of children. In addition to these control variables, Heckert et al. (1998) also included income-to-needs ratio as a socioeconomic indicator and difference in health status of husband and wife in their study on marital dissolution.

For my dissertation, I selected the most commonly used control variables in the literature on marital dissolution. For conceptual reasons and to facilitate my analysis on the odds of divorce, I grouped these variables into resource dependencies, labor dependencies, developmental dependencies, and control variables, following Heckert et al.'s (1998) and Nock's (2001) sequential construction of the Logistic Regression Model by blocks of covariates.

The first resource dependency is educational homogamy, which is basically a proxy for the difference in educational level between husband and wife. According to the PSID code books (http://simba.isr.umich.edu/VS/s.aspx), these levels are: 1 = 0-5 years of education; 2 = 6-8 years; 3 = 9-11 years; 4 = 12 years; 5 = 12 years plus some nonacademic training; 6 = some college, but not degree; and 8 = college and advanced or professional degree. This variable compares the educational level of husband and wife, and has four different categories: (1) same educational level; (2) the husband's educational level was two levels higher than the wife's; (3) the husband's educational level was three or more levels higher than the wife's; and (4) the wife's educational level was two or more levels higher than her counterpart's.

The second covariate included in my analysis is health dependency of husband and wife as perceived by the husband. The responses for the perceived health status for the husband and also for the wife ranged from excellent perceived health (5) to poor (1). This dependency was calculated by subtracting the perceived health of the wife from the perceived health status of the husband. Since both variables have five categories, the range for health dependency goes from -4 to 4, which was treated as an interval ratio variable. According to the PSID code books, the perceived health variables for husband and wife were not gathered prior to 1985. Because of this, health dependency was not included for the first three periods of analysis (1968-1972, 1973-1977, and 1978-1982).

In regard to the labor dependencies, I included two variables in my study: percentage of weekly hours of housework contributed by wife, and husband's percentage of weekly hours of paid labor. According to South (2001), prior studies indicated that socioeconomic status and employment stability are inversely related to the likelihood of divorce. Furthermore, Nock (1995) argued that these covariates are indicative of the relative degree of dependence or independence of husband and wife.

For almost all the years included in the PSID study (until 1993 and then again in 2003), the percentage of hours worked by husband and wife are reported on an annual basis. There is, however, a proxy for weekly worked hours for husband and wife reported in 1997 (the last year of the 1993-1997 file), which needed to be converted into an annual variable (by multiplying it by 52) to make it comparable to the variable percentage of hours worked for previous years. As for the percentage of weekly hours of housework contributed by wife, the opposite is true. Starting in 1976, the PSID gathered hours of housework for both husband and wife on a weekly basis. Prior to 1976, however, the PSID only reported annual hours of housework. Therefore, the appropriate transformation was carried out to make this variable comparable across all the five-year periods under study.

With respect to the developmental dependencies, years married constituted a challenging variable to be included in my analysis because year of first marriage was reported by the PSID in 1976 and 1985 only. In order to incorporate this variable for the remaining five-year periods (with the exception of 1968-1972), a forward assignment was carried out according to the following rationale: a categorical variable consisting of three categories (missing system, two years, and more than two years) was created as a proxy of years married for 1983-1987. This variable identified whether the wife married in 1985 or whether she was married prior to 1985. In the first case, the wife could only be married for two years, since 1987 minus 1985 equals two. In the second option, she had to be married for more than two years. The third category (missing system) was created because every forward assignment of a covariate generates missing values, since new couples are continuously incorporated to the PSID dataset who did not have data for 1985 or prior to this year. The same logic was applied for 1988-1992 (missing system, seven years, and more than seven years) and 1993-1997 (missing system, 12 years, and more than 12 years). The omitted reference group for the logistic regression analysis was the wives married in 1985. Furthermore, the same procedure was used to estimate years married for 1973-77 and 1978-1982, based on the variable year of first marriage reported in 1976.

The second developmental dependency is age of youngest child, which was collapsed into three categories: youngest child between 3 and 17 years old, no children currently living at home, and youngest child less than 3 years old. The last group served as the reference group. The last developmental dependency was the age difference between husband and wife, which was operationalized by creating four different groups: husband one to three years older than wife, husband four to five years older, husband six years older, and wife two or more years older. Age homogamy was included as the reference group. Both age of youngest child, and age difference between husband and wife have values for all relevant years (1968 to 1997).

Finally, I included wife's age at first marriage, income to needs ratio, race, wife's religious affiliation, and husband lived with both parents as child as control variables in the multivariate logistic analysis. As stated above, the variable wife's year of first marriage is only available for 1976 and 1985. For this reason, I estimated the wife's age at first marriage for 1972-1977 and 1982-1987 according to the following equations:

$$\text{Years Married}_{(1977)} = 1977 - \text{Year of first marriage} \qquad (1)$$

$$\text{Years Married}_{(1987)} = 1987 - \text{Year of first marriage} \qquad (2)$$

$$\text{Wife's age at first marriage} = \text{Age in 1977} - \text{years married}_{(1977)} \qquad (3)$$

$$\text{Wife's age at first marriage} = \text{Age in 1987} - \text{years married}_{(1987)} \qquad (4)$$

As becomes clear from equations 1 to 4, year at first marriage is a fixed variable, whereas years married$_{(year)}$ is a continuous variable. Despite the fact that wife's age at first marriage is the same regardless of the year for which it is calculated, I included both calculations for 1977 and 1987 (the last years of 1973-1977 and 1983-1987, respectively) because new individuals were incorporated to the PSID dataset after 1976.

The variable income to needs ratio, which measures the socioeconomic status of the household, was not gathered for 1997. Because of this, I estimated a proxy of income to needs ratio for 1997, dividing the 1996 total family income reported in 1997 by the1996 family needs reported in 1997.

Race was controlled by creating four different categories: White-White couples, Black-Black couples, White-Black couples, and Black-White couples. The first group was entered as the reference group. The relatively small number of divorce cases in households where the race of husband and wife is other than White or Black forced their exclusion from this analysis. Despite the fact that the race of head was gathered for all the years included in the PSID study, race of wife was only gathered from 1985 on. For this reason, I made a backwards assignment of the 1985 variable for 1968-1972, 1973-1977, and 1978-1982. The same procedure holds true for wife's religious affiliation. This variable is available for 1976, and for 1985 and after; therefore, a backwards assignment was required as well. Heckert et al. (1998) modeled this variable by creating four broad categories: Protestant, Catholic, Jewish and other non-Christian, and no religion. The first category was used as the reference category. Finally, whether the husband lived with his parents until the age of 16 was included in the analysis as a dummy variable. This last variable was also available since 1985 only, so a backwards assignment was carried out as well.

Operationalization of the Couples' Income Ratio

There are different ways to operationalize the income variable for modeling income dynamics. For example, the husband's or the wife's annual income could be used separately or the couple's income ratio could be used instead. The husband's and wife's income ratio, however, appears to be the best construct because it incorporates income fluctuations for both husband and wife in one single statistic. Rogers (2004) utilized both the wife's actual income and the wife's income as a percentage of the total family income to test the four economic models introduced in the literature review section of my dissertation. Both the Economic Independence Model and the Economic Partnership Model used the wives' actual income, whereas the Role Collaboration Model and the Equal Dependence Model used the wife's percentage of family income as their independent of interest. The selection of the appropriate independent variable was not random; the models that depict a close collaboration or an economic dependence between spouses require the income ratio—instead of the actual income—to model the exchange in the role as breadwinner of husband and wife which is at the heart of income instability. Drago et al. (2004) argued that the income ratio is the best variable to identify couple's income fluctuations in longitudinal studies.

For these reasons, the husband's percentage of income ratio (husband's actual income divided by total income) was chosen as the independent variable of interest in my dissertation. This ratio provides the same information as its counterpart, the wife's percentage of income, and is easier to build with the income data provided by the PSID. The range of this ratio goes from zero to one, with zero indicating that no income was provided by the husband and one showing that the husband was the sole breadwinner. Additionally, the income ratio does not need to be corrected for inflation when comparisons are made across time.

Operationalization of the Couples' Income Ratio Instability

As stated previously in the literature review, only a few studies address the impact of income resources on the odds of divorce. The findings of those studies are inconclusive at best, and often times go in opposite directions. None of these studies, however, have modeled the impact of income instability—defined as erratic fluctuations in the couples' income ratio with no identifiable pattern—on the likelihood of divorce.

One of the challenges of modeling income instability is the lack of appropriate tools to depict erratic income fluctuations. In order to overcome this problem, it is important to devise a different approach or use statistical techniques other than the traditional linear or curvilinear models that are generally used in the literature on income dynamics and marital dissolution. The underlying idea of this argument is that linear and curvilinear models are adequate for depicting patterns or data trends, but inappropriate for modeling erratic fluctuations. In the next section of this dissertation, several approaches are discussed and a final recommendation is made to determine the best method for modeling income instability based on the relative strengths and weaknesses of the methods presented below.

Standard Deviation

In addition to the range, the most basic statistic that measures dispersion is the standard deviation. This statistic could be used as a proxy for income fluctuations. Originally, a five-year moving standard deviation was considered to operationalize income dispersion. This type of standard deviation is suitable for longitudinal studies that have a person-year structure because it does not violate one of the three tenets to determine causality: the independent variable needs to precede the dependent variable. In these studies, the information of a given variable gathered throughout the years is collapsed into a single column where the yearly value of this variable becomes another input of this column. In other words, the data that were originally arranged in several columns (one column per year) is collapsed into one single column. This is the data structure that was used, for example, by Heckert et al. (1998) to built a Logistic Regression Model to test the impact of relative earnings of husbands and wives on the likelihood of divorce. For this dissertation, however, a different data structure will be used that does not require the construction of person-year files. The income instability estimated for the first five years will be the basis to determine the impact on the odds of divorce in the sixth year. The rationale for this five-year structure was explained in detail in the previous section of this chapter, “Data Management and Merging Process”. In other words, every five-year cross-year family/file will actually include six years worth of information. With this file structure, though, a simple standard deviation will suffice to capture income.

Latent Pathway Analysis

As previously discussed in the literature review, another alternative for modeling income instability is Latent Path Analysis. According to Macmillan and Copher (2005), Latent Path Analysis identifies types or subtypes of related cases from multivariate categorical data, much like cluster analysis does with ordinal and interval ratio data. The latent constructs in this model are the different groups that cannot be observed directly. More formally, traditional Latent Class Analysis assumes that each observed variable is independent from other variables within the same latent group. This is called conditional independence (Copher). The model actually calculates the probability of belonging to a latent group. Specifically, it estimates the unconditional probabilities of belonging to each latent class and the conditional response probabilities of the observed variables given that latent class.

One possible avenue for applying Latent Path Analysis to income instability is to conceptualize husband-wife income ratios as belonging to different latent (unobserved) groups with stable or unstable fluctuations during each five-year period from 1968 to 1997. For example, a stable fluctuation will include income ratios where the husband earns consistently more than the wife. On the other hand, an unstable fluctuation will include income ratios where husbands and wives continuously exchange roles as the main breadwinner. Once the observed variables are fed into the model, a selection process needs to be developed to single out the pathways that fit the data best. Since there are an incredibly large number of possible pathways (Macmillan & Copher, 2005), Chi-

Square tests and the Bayesian Information Criterion (BIC) could be used to select the best latent pathways. It is important to remember that these pathways actually depict the unconditional probability of belonging to a latent class and the conditional response probabilities of the income ratios. For example, one manifest (observed) variable yields the following model:

$$\pi it = \pi tX \ \pi it \ IR/X \qquad (5)$$

where πtX denotes the probability of belonging to latent class t = 1,2,…T of latent variable X; and πit IR/X denotes the conditional probability of obtaining the ith response to variable Income Ratio (IR) from members of class t, i = 1,2…I. The resulting probability graphs will show which of these latent pathways are more prevalent, and also the possible transitions from one pattern to another. Once these latent pathways and transitions are identified, they could be coded and fed into a Cox Regression Model or Logistic Regression Model along with control variables to estimate their impact on the odds of divorce.

Combinations Algorithm

A third alternative for modeling income instability is to create an algorithm that identifies couples with unstable income trends. The underlying logic of the algorithm is simple: to differentiate couples' income ratios that are erratic from income ratios that show clear patterns such as the husband earning consistently more than the wife or the wife earning more than the husband. If, for the sake of the argument, the PSID dataset contained only ten couples with five years worth of data, a careful visual inspection would be enough to single out the couples with unstable income ratios. This selection would require a definition of income instability and the formulation of categories to operationalize the referred definition. In reality, however, the PSID dataset contains income information from almost 8,000 couples (with the additional complications of attrition and replacement) and 30 years worth of data. For this reason, it is necessary to create an algorithm to carry out the selection process.

This algorithm could be written in SPSS syntax and be based on the same rationale that Drago et al. (2004) used to differentiate temporary from persistent female breadwinner families. Drago et al. used the first two waves of the Household, Income and Labor Dynamics in Australia (HILDA) Survey to assess whether temporary female breadwinner families differ on various family and individual characteristics from persistent female breadwinner families. Three basic categories were defined for the study: male breadwinner, female breadwinner, and couples with basically the same level of income. The last category included couples where either the male or the female breadwinner earned no more than 10% of the spouse’s income. Since Drago et al. had only income information for two years, the following rationale was used to identify the different categories: if the wife earned more that her husband in both years, this couple was considered as a persistent female breadwinner family. On the other hand, if the wife earned more than her husband in one year but not in the next year, this couple was assigned to the group of the temporary female breadwinner families.

In order to model income instability, I will use the four categories of couples developed by Heckert et al. (1998): traditional couples (husband earns from 75% to 100% of household income), new traditional couples (50 % to less than 75%), nontraditional couples (25% to less than 50%) and reverse traditional couples (zero to less than 25%). The rationale behind the use of these categories is that they constitute an easy way to track changes in the income ratio through time. Since this algorithm constitutes a novel contribution to the literature in marital dissolution, its structure needs to be parsimonious. The modeling of income instability will encompass 30 years worth of data divided into five-year periods, where the different degrees of income instability will be identified according to a rationale similar to Drago et al. (2004). For instance, if the couple's income ratio shifts either up or down from its original category for only one year (out of the four years where the income ratio could vary, since the first year is the reference year), then this trend will constitute a first degree of instability. If there is a shift for two years, the income ratio fluctuation will show a second degree of variability. A three-year shift will entail a third degree of instability, and finally, a four-year shift will denote a fourth degree of instability (the highest level of instability that the algorithm could measure). The exception to this procedure occurs when there is a shift of the income ratio in all four years to a specific category different than the initial one. In that case, the income ratio will be recoded as stable pattern with temporal variability (the temporal variability actually occurs in the first year, which is the reference year for modeling income instability).

The algorithm for modeling income instability was based on the Theory of Permutations and Combinations. According to the *Encyclopedia Britannica* (www.britannica.com/), an algorithm usually means a procedure that solves a recurrent problem. Specifically, an algorithm is a systematic procedure that produces, in a finite number of steps, the answer to a question or the solution of a problem starting with an initial state and ending with a final state. In this case, the initial state is the classification of the husband-wife income ratios in the categories developed by Heckert et al. (1998). The second state encompasses the coding of the husband-wife income ratios according to the degree of income instability they showed during each five-year period. The last state includes the recoding of the income ratios that vary consistently in the same category for four years in a row.

Since there are a finite number of possible variations of the income ratio from its original category, the following formula of permutations was used:

$$n\_P\_k = n!/(n-k)! \qquad (6)$$

where n_P_k represents the number of permutations of K objects from a set of n objects and n! is n factorial. If, for example, we want to find the number of ways to arrange the three letters in the word PET in different two-letter groups where PE is different from EP and there are no repeated letters, we will have the following permutations:

PE PT ET EP TP TE

$$3\_P\_2 = 3!/(3-2)! = 3!/1! = 3*2*1/1 = 6$$

For the purposes of my dissertation, however, PE equals EP because, according to the algorithm, both will be assigned the same code. In other words, order does not matter when modeling income instability with this parsimonious algorithm. If the income ratio for the second year moves to a higher category—compared to the value in the initial year—and the income ratio for the third year drops to a lower category, the algorithm will assign a second degree of instability to this case. The same is true, however, for the case in which the income ratio goes down in the second year and goes up (from the initial category) in the third year. For this reason, the formula of combinations (where order does not matter) was used instead:

$$n\_C\_k = n!/[k!(n - k)!] \tag{7}$$

where n_C_k represents the number of combinations of K objects from a set of n objects and n! represents n factorial. In the previous example, there are only three possible combinations of two-letter groups without repeated letters:

PE PT ET

$3\_C\_2 = 3!/[2!(3-2)!] = 3!/2! = 3*2*1/2*1 = 3/1 = 3$

Since the income ratios are allowed to vary in four years out of five (because the first year represents the original category), n equals four and k can assume the values of one to four (see Table 1). If there is only one variation of the income ratio above or below the original category, these are the possible combinations:

Table 1

Number of Combinations of the Income Ratio for n=4 and k=1

Variation	Year 1	Year 2	Year 3	Year 4
1	X	--	--	--
1	--	X	--	--
1	--	--	X	--
1	--	--	--	X

Note. X represents a variation of the income ratio–either up or down–from the original category. -- means no variation from the original category.

According to the formula, the number of possible combinations for only one income ratio variation is:

4_C_1 = 4!/[1!(4! -1)!] = 4!/1! 3! = 4*3*2*1/1*3*2*1 = 4/1 = 4

In the case of two variations, the possible number of combinations increases to six as shown in Table 2.

4_C_2 = 4!/[2!(4 – 2)!] = 4!/2! 2! = 4*3*2*1/2*1*2*1 = 6

Table 2

Number of Combinations of the Income Ratio for n=4 and k=2

Variation	Year 1	Year 2	Year 3	Year 4
2	X	X	--	--
2	--	--	X	X
2	X	--	X	--
2	--	X	--	X
2	--	X	X	--
2	X	--	--	X

Note. X represents a variation of the income ratio–either up or down–from the original category. -- means no variation from the original category.

With three variations, the number of possible combinations goes down to four (see Table 3).

$4\_C\_3 = 4!/[3! (4 – 3)!] = 4!/3! 1! = 4*3*2*1/3*2*1*1 = 4$

Table 3

Number of Combinations of the Income Ratio for n=4 and k=3

Variation	Year 1	Year 2	Year 3	Year 4
3	X	X	X	--
3	X	X	--	X
3	X	--	X	X
3	--	X	X	X

Note. X represents a variation of the income ratio–either up or down–from the original category.
-- means no variation from the original category.

Finally, if the income ratio varies during all four years, there is only one combination possible as indicated in Table 4:

Table 4

Number of Combinations of the Income Ratio for n=4 and k=4

Variation	Year 1	Year 2	Year 3	Year 4
1	X	X	X	X

Note. X represents a variation of the income ratio–either up or down–from the original category.

The use of the Theory of Combinations allowed including all possible variations of the income ratio during a four-year period, so no income ratio variation was left outside the algorithm. The SPSS syntax that I wrote for 1968 to 1972 (with an initial category of income ratio >=0 and < 25%), which includes four degrees of income instability, is presented below:

```
*******************(0.25>ratio>=0.00) First Degree of Instability [1968-1972]***

Stable Pattern =1
First Degree of Instability = 2
Second Degree of Instability = 3
Third Degree of Instability = 4
Fourth Degree of Instability = 5

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25) and (ratio_70
>= 0.00 and ratio_70 < 0.25)
and (ratio_71 >= 0.00 and ratio_71 <0.25)  and (ratio_72 >= 0.00 and ratio_72
<0.25)) income_instability = 2 .
EXECUTE.

**************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.00 and ratio_69 <
0.25) and (ratio_70 >= 0.25)
and (ratio_71 >= 0.00 and ratio_71 <0.25)  and (ratio_72 >= 0.00 and ratio_72
<0.25)) income_instability = 2 .
EXECUTE.

**************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.00 and ratio_69 <
0.25) and (ratio_70 >= 0.00 and ratio_70 < 0.25)
and (ratio_71 >= 0.25)  and (ratio_72 >= 0.00 and ratio_72 <0.25))
income_instability = 2 .
EXECUTE.

**************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.00 and ratio_69 <
0.25) and (ratio_70 >= 0.00 and ratio_70 < 0.25)
and (ratio_71 >= 0.00 and ratio_71 <0.25)  and (ratio_72 >= 0.25))
income_instability = 2 .
EXECUTE.

*******************(0.25>ratio>=0.00) Second Degree of Instability [1968-1972]***

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25) and (ratio_70
>= 0.25)
and (ratio_71 >= 0.00 and ratio_71 < 0.25)  and (ratio_72 >= 0.00 and ratio_72 <
0.25)) income_instability = 3 .
EXECUTE.
```

```
************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.00 and ratio_69 <
0.25) and (ratio_70 >= 0.00 and ratio_70 < 0.25)
and (ratio_71  >= 0.25)  and (ratio_72 >= 0.25)) income_instability = 3 .
EXECUTE.

************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25) and (ratio_70
>= 0.00 and ratio_70 < 0.25)
and (ratio_71 >= 0.25)  and (ratio_72 >= 0.00 and ratio_72 <0.25))
income_instability = 3 .
EXECUTE.

************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.00 and ratio_69 <
0.25) and (ratio_70 >= 0.25)
and (ratio_71 >= 0.00 and ratio_71 <0.25)  and (ratio_72 >= 0.25))
income_instability = 3 .
EXECUTE.

***********************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25) and (ratio_70
>= 0.00 and ratio_70 < 0.25)
and (ratio_71 >= 0.00 and ratio_71 < 0.25)  and (ratio_72 >= 0.25))
income_instability = 3 .
EXECUTE.

***********************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.00 and ratio_69 <
0.25) and (ratio_70 >= 0.25)
and (ratio_71 >= 0.25)  and (ratio_72 >= 0.00 and ratio_72 < 0.25))
income_instability = 3 .
EXECUTE.

******************(0.25>ratio>=0.00) Third Degree of Instability [1968-1972]***

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25) and (ratio_70
>= 0.25)
and (ratio_71 >= 0.25)  and (ratio_72 >= 0.00 and ratio_72 < 0.25))
income_instability = 4 .
EXECUTE.
```

```
*************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25) and (ratio_70
>= 0.25)
and (ratio_71 >= 0.00 and ratio_71  < 0.25)  and (ratio_72 >= 0.25))
income_instability = 4 .
EXECUTE.

*************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25) and (ratio_70
>= 0.00 and ratio_70 < 0.25)
and (ratio_71 >= 0.25)  and (ratio_72 >= 0.25)) income_instability = 4 .
EXECUTE.

*************************************************

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.00 and ratio_69 <
0.25) and (ratio_70 >= 0.25)
and (ratio_71 >= 0.25)  and (ratio_72 >= 0.25)) income_instability = 4 .
EXECUTE.

******************(0.25>ratio>=0.00) Fourth Degree of Instability [1968-1972]***

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25) and (ratio_70
>= 0.25)
and (ratio_71 >= 0.25)  and (ratio_72 >= 0.25)) income_instability = 5 .
EXECUTE.

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.75) and (ratio_70
>= 0.75)
and (ratio_71 >= 0.75)  and (ratio_72 >= 0.75)) income_instability = 1 .
EXECUTE.

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 >= 0.50 and ratio_71 < 0.75)  and (ratio_72 >= 0.50 and ratio_72 <
0.75)) income_instability = 1 .
EXECUTE.

IF ((ratio_68 >= 0.00 and ratio_68 < 0.25) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 >= 0.25 and ratio_71 < 0.50)  and (ratio_72 >= 0.25 and ratio_72 <
0.50)) income_instability = 1 .
EXECUTE.
```

Please refer to Appendices A, B, and C for the remaining syntax for 1968-1972. As listed above, the syntax was written as a series of conditional formulas to model income ratio instability. The coding goes from one to five, where one indicates a stable income ratio and five stands for the highest level of income instability that the algorithm can identify. Since the code "one" represents the absence of instability, the remaining four codes (two to five) actually model the four degrees of income instability of the combinations algorithm. For instance, as shown in the syntax listed above, the first degree of instability (only one variation in four years worth of data) includes four conditional equations (4_C_1 = 4), the second degree of instability has six conditional equations (4_C_2 = 6), and the third degree of instability includes four (4_C_3 = 4). The fourth degree of instability, nevertheless, has four conditional formulas instead of one (4_C_4 =1). The reason for the remaining three equations is the recoding of the variations of the income ratio that occur within a given category during all four years. For example, If the initial income ratio is in the fist category (zero to less than 25%), and then changes to a different category (e.g. 50% to less than 75%) for the subsequent four years, its code changes from five to one. The same reasoning holds true for the remaining categories. The rest of the syntax presented in Appendices A, B, and C includes the other three "initial" categories for 1968-1972 (25% to less than 50%, 50% to less than 75%, and 75% to 100%).

It is important to note that this algorithm identifies couples with different degrees of instability and, because of this characteristic; comparisons among couples with different degrees of income instability are possible. For instance, following the same logic as the U-shaped Collaborative Model (Oppenheimer, 1997)—where the likelihood of divorce was the highest among wives earning too much or too little of the total household income—this new algorithm will allow comparisons within couples where husband and wife exchange their role as the main breadwinner. Once the different degrees of income ratio instability are identified, the coding can be fed into a Logistic Regression Model to assess the impact of income ratio instability on the odds of divorce.

Structural Equation Model

As noted in the literature review, another mechanism to identify income ratio fluctuations is the Latent Growth Curve Model (LGC). There are different ways to build a Latent Growth Curve Model—for example, Structural Equation Modeling. As compared to other well-known models like the Hierarchical Linear Model, this approach is a good fit to build a LGC because of the flexibility it offers in specifying the relationships between latent, observed variables, and weights (Hoyle, 1995). These two models, as well as their main characteristics, are briefly presented below.

According to Hoyle (1995), Structural Equation Modeling is a comprehensive statistical approach to test hypotheses about the relationships among variables. These variables can be observed, latent, endogenous, exogenous, directional or non-directional. The major difference among Structural Equation Models (SEM), Ordinal Least Squares Models (OLS) and standard ANOVA analysis is the great flexibility that SEM enjoys in specifying statistical models. For instance, the response variable in one regression equation of SEM may appear as the predictor in another equation. Indeed, variables in SEM may influence one another reciprocally, or through other variables as intermediaries.

Hoyle (1995) highlighted the similarities and differences between SEM and standard approaches such as correlation, multiple regression, and ANOVA. For example, the latter models are based on linear statistical models. Actually, multiple regression, factor analysis, and ANOVA are special instances of the more general SEM. Additionally, statistical tests of these linear models (including SEM) are valid only if certain assumptions are met. These assumptions are independent observations and multivariate normality. The most important similarity among these models, nevertheless, is that they do not offer a statistical test for determining causality. This is especially misleading in SEM because the path diagrams (the arrows from one variable to another) are confused with causal relations.

To establish causality, three conditions must be met: the independent variable precedes the dependent variable, isolation, and directionality. The latter requirement is difficult to meet because it cannot be tested statistically by any linear model. Therefore, directionality should stem from logic and sound theory, not from statistical design. To complicate things further, there may be different—even opposing theories—explaining the causal relationship between two or more variables. On the other hand, according to Hoyle (1995), there are two major differences among the statistical models described above. First, SEM requires formal specification of a model. Second, unlike ANOVA that evaluates the main and effect and interaction hypotheses, and multiple regression analysis that allows only the specification of direct effects on a single outcome variable, SEM does not require any particular model specification. SEM also places few restraints on what types of relationships can be specified. And, finally, only SEM can estimate and test hypotheses between latent variables.

Latent Growth Curve Model

According to Duncan et al. (1999), latent growth analysis is a method to study change. There are many questions that can be asked regarding change. For example: How do people change? What explains how much people change? What reduces adverse effects? What optimizes positive results? Traditionally, researchers have used static data to answer these questions. The modeling of change can only be appropriately carried out, however, with longitudinal models such as the Latent Growth Curve Model.

There are many aspects of change that should be taken into account (Duncan et al., 1999). It is important to bear in mind that change can be positive or negative. Change can also be linear (such a straight line) or curvilinear. Therefore, this model allows for testing the linearity hypothesis. For this, the model requires at least three data points because any straight line will perfectly fit two data points. In the case of only two points, there is not enough information to prove or disapprove the linearity of the data; in other words, there are not degrees of freedom to test the linearity hypothesis.

The main components of the Latent Growth Curve Model (Duncan et al., 1999) are the intercept and the slope. They are usually represented as ovals in a graphical display of the model. Both the intercept and the slope are latent variables (free of measurement error) and exogenous variables. As such, they have arrows pointing towards the measured data showing that they exert a directional effect on their corresponding indicators. The intercept is a concept difficult to grasp because it is different than the algebraic concept of a y-intercept. In a Latent Growth Curve Model, the intercept is no longer the value of the dependent variable when the independent variable adopts a value of zero. Instead, it becomes the initial level of the latent curve. This initial level is actually the average initial level of the different individuals participating in the study. This is why the arrows pointing from the intercept to the different data points (observed variables) have a value of one attached to them. This means that all data points share the same initial level.

On the other hand, the slope has arrows pointing towards the data points with weights ranging from zero to three (in a study with four data points corresponding to four sequential years). The first weight assumes a value of zero because there is no growth in the initial year. The subsequent weights increase by one, indicating a linear growth. If the growth was modeled as curvilinear, for example, the weights would assume values of zero, one, four, and nine, respectively. According to Duncan et al. (1999), some researchers only set values for the first two weights and let the model estimate the remaining weights. This allows for a very complex growth model to emerge.

There are two additional components of the Latent Growth Curve Model. These are the variances and covariances of the latent constructs. As discussed in the previous section on SEM, there are three parameters in a Structural

Equation Model: the weights that show directional influences, the variances of exogenous variables, and the covariances of exogenous variables (Hoyle, 1995). The covariance is usually represented by a two-arrow line pointing towards the intercept and the slope. This two-arrow line represents the nondirectionality of the covariance of two exogenous variables, the intercept and the slope.

In summary, the Latent Growth Curve Model is an appropriate technique for modeling latent constructs such as latent patterns of the relative income of husband and wife. This model is adequate for building linear or curvilinear latent curves instead of stochastic income ratio fluctuations. Nevertheless, there is one exception to this argument. If the Latent Growth Curve Model is used in a nontraditional way, it would be suitable for depicting erratic fluctuations. Generally, the Latent Growth Curve Model is used to estimate the initial level and the slope of the latent construct being analyzed and to test if the initial level, the slope, or both have a significant effect on other variables.

It is important to bear in mind that the Latent Growth Curve Model also includes the error terms of the observed variables. These error terms are latent constructs themselves, and can also exert a directional effect on other variables. If the error term is conceptualized as capturing the random fluctuations of the observed variable, it is possible to test whether these random fluctuations have a significant effect on a dependent variable such as the hazard of divorce. There is one caveat to this conceptualization, however. The hazard of divorce is a bivariate variable, and therefore cannot be used within the framework of the Latent Growth Curve Model because this model requires that the observed variables, covariates, and dependent variables should be interval ratio variables. If the dependent variable were an interval ratio variable, it would have been appropriate to model income ratio instability with this model.

Selection of the Best Methodology for Modeling Income Ratio Instability

Several procedures to model income ratio instability were presented above. The next step consists of determining the best mechanism to depict income ratio fluctuations. As stated previously, the standard deviation of the income ratio is a good proxy for income ratio variability. This statistic is universally used as a measure of dispersion. The main benefit of using the standard deviation is parsimony; it is fairly easy to calculate and include in a Proportional Hazards Model to determine its effect on the odds of divorce. Additionally, there is no need to estimate a moving standard deviation—which would impose a heavy burden on the merging scheme of the five-year cross-year/individual files—because the proxy of income ratio instability for the first five years will be used to estimate the odds of divorce in year number six. In other words, the likelihood of divorce in $year_n$ is not determined by the income ratio instability in $year_{(n-1)}$ but instead from the previous five years.

The Latent Path Analysis, on the other hand, allows identifying the most common income ratio pathways that could later be included in a Proportional Hazards Model to determine their impact on the likelihood of divorce. This analysis permits a more sophisticated modeling of the income ratio instability than the crude standard deviation, albeit it is a more complex procedure. This is especially true when it comes to determining the pathways that best fit the data.

The immense number of possible pathways requires a complex algorithm for the selection of the most prevalent pathways such as, for example, the Bayesian Information Criterion (Macmillan & Copher, 2005).

The third mechanism to model income ratio instability is the algorithm based on the Theory of Combinations. The advantage of this procedure is the identification of the different degrees of instability, starting from no variation of the income ratio—with respect to the original category in the first year—to a full variation in the remaining four years. The Theory of Combinations allows the identification of all possible variations of the income ratio with a lower degree of complexity than the Latent Pathway Analysis. Its shortcoming, however, is the determination of the different categories of the income ratio. The four categories selected represent an arbitrary number of categories to measure income ratio instability. I could have identified five or six categories for the same purpose. If the income ratio changes from the upper level of the first category to the lower level of the second, this variation may be very small percentage-wise, but the algorithm would assign a different level of income instability to that particular case.

Finally, the last procedure considered was the Latent Growth Curve Model within the framework of Structural Equation Modeling. The few constraints that this model places on variables allow for modeling both the income ratio instability and its effect on the odds of divorce in the same model. In other words, there is no need to use a second model to test my hypotheses. The pitfall of this approach is not the model itself nor its assumptions, but rather the type of dependent variable that is being used. The odds of divorce is a bivariate (or survival) variable with only two possible outcomes. On the contrary, Latent Growth Curve Analysis requires that all variables included in the model must be interval ratio.

After a careful evaluation of the strengths and weaknesses of the procedures described above, the Combinations Algorithm was selected as the best mechanism for modeling income ratio instability. After an extensive review of the literature on divorce in Chapter II, no model depicting the effect of income ratio fluctuations on the odds of divorce emerged from the analysis. In this sense, the Combinations Algorithm constitutes a true contribution to the body of knowledge on income instability and divorce. Despite the fact that this algorithm includes four categories for modeling income ratio instability, it represents a first approach to identifying different degrees of income ratio instability. In the future, it may be possible, however, to develop a more sophisticated algorithm or statistical model able to depict more subtle income ratio variations. Furthermore, it is possible to ameliorate the efficacy of the algorithm by multiplying the standard deviation with the income ratio instability variable (the final outcome of the Combinations Algorithm). The underlying idea of this multiplication is to estimate the interaction effect of the five-year standard deviation and the income ratio instability variable. This interaction effect will smooth out the sudden jumps of the income ratio from the upper limit of a given category to the lower limit of the next one, or vice versa.

CHAPTER IV

IMPACT OF INCOME RATIO INSTABILITY ON THE ODDS OF DIVORCE

Once I identified the best methodology for modeling income ratio instability, the next step included identifying the best model to assess the impact of the income ratio instability on the odds of divorce. Since the dependent variable is a survival variable (only two possible outcomes), three survival models—the Kaplan Meier Model, the Cox Regression Model, and the Logistic Regression Model—are introduced in Chapter IV.

Kaplan-Meier Model

The Kaplan-Meier Model is a popular method of survival analysis. As noted in the literature review, this model is a Proportional Hazards Model that is widely used in the literature on marital disruption. The term survival analysis can be misleading because it is a technique for analyzing time-to-event or failure-time data, which is not necessarily related to survival or death in the usual sense (Norusis, 1994). This model can also be used to analyze events other than death, such as time to degree completion, or time to divorce. Both degree completion and divorce can be considered as the end point or “death” of a student or marital life. In this sense, they can be treated in the same fashion as natural death.

The great advantage of Kaplan-Meier and other proportional hazards models with respect to ordinary least squares models is that they include censored cases in their analysis. Cases for which the event does not occur during the study are called censored cases. According to Norusis (1994), there are two sources of censoring. For instance, a subject could be lost to follow-up. The subject was known to be alive at the last contact, but there is no information as to whether he or she is dead or alive in subsequent contacts. Besides, a research study could finish after a fixed period of time and some of the subjects could be still alive at the end of the study.

Censoring time is a useful piece of information because it affects the cumulative survival probability of two or more groups of individuals. Indeed, the Kaplan-Meier Model generates survival curves—based on the cumulative survival probability—of two or more groups, such as a clinical and control groups, and tests whether the curves are statistically different from each other. Norusis (1994) showed that SPSS actually uses the arithmetic reciprocal of the cumulative survival curve for running the model. This curve is known as the cumulative hazards curve. This curve is based on one fundamental assumption of proportionality of hazards. This proportionality is understood as similarity in survival—or death—among the groups. If the assumption of equality of survival is met, then the groups are comparable. What the model is really testing is, therefore, the difference between the observed and expected deaths within each group. One way to test the proportionality assumption is to plot the survival curves to see whether or not the curves intersect each other. If they cross each other, then there is a violation of the proportional hazards assumption.

Cox Regression Model

The advantage of the Cox Regression Model as compared to the Kaplan-Meier Model is that it allows for the inclusion of covariates in the analysis. In other words, with the Cox Model I can perform a multiple regression analysis using control variables and my independent of interest, income ratio instability. This is also a widely used Proportional Hazards Model in studies of marital disruption. The Cox Model also generates survival curves (or hazard curves), but the graphical analysis becomes cumbersome when several covariates are added to the model. Actually, the Cox Model creates an entire survival curve for each value of the independent variable (Norusis, 1994). The Cox Regression equation is:

$$S(t) = [S0\ (t)]^{p} \qquad (8)$$

where p = e(B*x)

S0(t) is the baseline survival function. It does not depend on the covariates; it only depends on time. This baseline survival function is similar to the constant variable of a Multiple Regression equation (Ordinal Least Squares) in that it serves as the reference value that increases or decreases depending on the relationship between the independent variables and the dependent variable (Norusis, 1994). On the other hand, the exponent (p) depends exclusively on the value of the beta coefficient and the value of the independent variable(s). SPSS uses the formula of the hazard function to run the Cox Model:

$$H\ (t) = [h0\ (t)] * p \qquad (9)$$

where p = e(B*x)

As is evident, this model is more parsimonious than the survival equation because the exponent (p) actually becomes a factor. Since the baseline hazard function is now multiplied by (p), the ratio of their hazards, for any two cases, will be a constant for all time points (Norusis, 1994). This is why this model is known as the Cox Proportional Hazards Model; the proportionality of hazards lies at the heart of this model. Norusis (1994) proposed different mechanisms to test the proportional hazards assumption. These tests include the Log-Minus-Log Survival Plot, the Martingale Residual Procedure, and the Cox-Snell residual Plot. If there is any suspicion that this assumption is being violated, the Time-Dependent Cox Regression Model should be used instead. In this model, (p) becomes more sophisticated because it includes an interaction between the independent variable and time. If this interaction is found to be significant, then the independent variable being considered is time-variant.

Logistic Regression Model

According to DeMaris (1995), logistic regression has become the technique of choice for modeling categorical dependent variables as well as latent constructs. As stated in the literature review, this is the most widely used model in the literature of family and marital dissolution. This model serves two main purposes. First, this model predicts group membership. Since logistic regression actually estimates the probability of success over the probability of failure ($P_{(success)}/P_{(failure)}$), the model's output is in the form of an odds ratio ($P_{(success)}/[1 - P_{(success)}]$). The odds ratio is a ratio of probabilities and it renders a simpler interpretation than the beta coefficients when assessing the impact of the covariates on the categorical dependent variable. Additionally, logistic regression also determines the strength of the relationships among variables, so that the beta coefficients are tested for significance for inclusion or elimination from the model.

In its most parsimonious version, the model predicts the probability of belonging to a group:

$$\pi = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k \quad (10)$$

DeMaris (1995) argued that this expression, which represents a linear regression model, faces several difficulties. Its most serious pitfall is that the expression on the right side of equation 5 is not bound to fall between zero and one. Clearly, the probability of an outcome cannot assume values outside the range of one to zero. For this reason, the odds ratio formula with logit transformations is used instead:

$$\log \pi/(1- \pi) = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k \quad (11)$$

$$\pi/(1- \pi) = \mathrm{Exp}^{(\alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k)} \quad (12)$$

where the probability of group membership (π) =

$$\mathrm{Exp}^{(\alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k)} /[1 + \mathrm{Exp}^{(\alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k)}] \quad (13)$$

Since an exponential function (exp) can assume values from zero to infinity, the right hand expression in equation 13 is clearly bound to the one to zero range. For instance, when the exponential function approaches zero, the expression becomes zero (0/[1+0]) = 0; when it approaches infinity, it becomes one (infinity/[1+infinity] = 1).

As stated previously, it is possible to interpret the results in terms of predicted probabilities or odds ratios (DeMaris, 1995). For example, predicted probabilities are useful when the objective of the model is to predict the probability of an event or group membership. If we are interested in the impact of the independent variables on the dependent variable net of control variables, on the other hand, the odds ratio is a better alternative. Nevertheless, this model also faces several numerical problems such as collinearity, complete separation (one or more covariates perfectly discriminates the outcome group), and zero cell count (especially with categorical covariates). Ramsey and Schafer (2002) proposed several alternatives to deal with these problems (e.g., running the model using OLS and requesting collinearity analysis, and collapsing categories to avoid cells with no data). If categorical variables are included in the analysis, it is also important to run contrasts among the different categories of these variables to determine which contrasts are significant and interaction effects to assess the combined effect of two covariates (such as the income instability variable and the standard deviation) on the dependent variable.

Selection of the Best Methodology for Modeling the Impact of Income Ratio Instability on the Odds of Divorce

As proposed by Teachman and Polonko (1984), proportional hazards models are the ideal fit for the analysis of family dissolution. This dependent variable is a survival variable and can be modeled as the likelihood of becoming divorced. As such, it has only two possible outcomes: the likelihood of becoming divorced and the likelihood of remaining married. Once the head of household divorces, his status will change to “divorced” and he will not able to change that status even if he remarries again, much like experiencing a “natural death”. From the two proportional hazards models introduced above, the best model to predict the odds of divorce is the Cox Regression Model. Unlike the Kaplan Meier Model, the Cox Regression Model allows for the inclusion of covariates in the analysis.

Nevertheless, there is one caveat when applying the Cox Regression Model to the present analysis. This limitation is not related to the model itself, but rather to design of the Combinations Algorithm. As explained previously, my analysis actually includes six years; the income ratio instability calculated for the first five years—net of the effect of control variables—is expected to influence the odds of divorce in the sixth year. This design implies that the dependent variable will have values for the sixth year only. On the other hand, the remaining variables (the independent of interest and the covariates) will have values for the first five years instead.

In order to estimate the Cox Regression Model, the time variable needs to be included as well. This variable tracks when the event (e.g., divorce or death) actually occurs. In the present dissertation, however, the time variable is limited to assume the value of six, since the marital status variable is only included for the sixth year. The impossibility of building the time variable renders the Cox Regression Model unsuitable for my dissertation. For this reason, the Logistic Regression Model is a better fit to assess the impact of the income ratio instability on the odds of divorce because this model does not require the construction of a time variable. Furthermore, logistic regression is adequate for modeling latent as well as categorical dependent variables.

CHAPTER V

RESULTS AND DATA ANALYSIS

The study of the impact of the income ratio of husbands and wives on the odds of divorce, encompassing a period of time that stretches for almost 30 years, generated a great deal of data. The PSID dataset includes more than 65,000 individuals and 8,000 families, with comprehensive labor, economic, and socio-demographic data. The challenge of the present chapter was, therefore, presenting the relevant findings in a clear, succinct, and orderly fashion.

The first step included a brief explanation of the characteristics of the five-year cross-year/ family files, as well as the reduction criteria they had experienced. This reduction process was necessary in order to meet the requirements of the conceptual model that assesses the influence of income ratio instability on the odds of divorce. A detailed explanation of the reduction criteria is formulated in the next section of the present chapter. Next, several income and income ratio charts are presented in order to show the main patterns of the family income and the income ratio of husbands and wives throughout 30 years, from 1968 to1997.

The last section included the logistic regression output for all six periods. A detailed explanation of the limitations, variable constructs, data collapsing, and inclusion and/or exclusion of covariates is also shown. It is important to bear in mind that every five-year period is unique in terms of the challenges each period presented. For instance, some key variables are included in some five-year periods, but not in all. Furthermore, some key covariates do not have enough data to run the Logistic Regression Model (e.g., zero cell count), so it was necessary to collapse some categories of these covariates or to exclude them from the analysis altogether. In other instances, the construct of a given covariate differed from previous constructs (in other five-year periods) because of the lack of data. Specifically, the major problem constituted the comparatively small number of divorce cases compared to married or cohabiting cases. This problem became evident when cross tabulations were run between the covariates in the model and the divorce variable. In these instances, some key variables showed cells with zero data in the cross tabulation tables, so a decision was made to recode, transform, or exclude covariates from the model. Overall, the most significant element of this section consisted on the evaluation of the hypotheses presented in chapter two. In other words, the logistic regression's output was utilized to support or contradict the hypotheses drawn from the present dissertation.

Features of the Five-Year Cross-Year/ Family Files

As stated in the introduction of this chapter, the original merged file (between the cross-year individual file and the family files) had more than 65,000 cases and required more than one gigabyte of storage capacity. This large file was divided into six five-year cross-year/ family files that covered 30 years of data. The reasoning behind splitting up this original file was conceptual more than practical. I wanted to model at least five years of income instability to assess its impact on the odds of divorce. In order to do so, the couples participating in the study had to be married during these five years. This was the first criterion for data reduction. Cases with single individuals or widowed, divorced, or separated couples were filtered-off from every five-year file. According to my conceptual model, couples were allowed to get divorced or separated in the sixth year only. For this purpose, an additional year including the marital status of the head of household was added to every five-year file.

The second criterion for data reduction was the relationship to head of household. Only heads of household were allowed to remain in every five-year file. This procedure not only dramatically reduced the size of the files, but also made the descriptive statistics more reliable. According to the merging scheme of the PSID dataset, the information of the family files (that pertains to the head of household only) should be merged to the cross-year individual file (which contains every individual who ever participated in the PSID study). This means that the labor and income information of the head of household was assigned to every member of the household. For this reason, the average family income was artificially inflated depending on the number of family members on each household. To avoid this pitfall, the elimination of the records of the family members (other than the head of household) was imperative.

For conceptual reasons, the couples where the husband is older than 55 years were also excluded from the five-year files. Since husbands older than 55 years approach retirement and may be the recipients of transfer funds, it becomes more difficult to model their income instability. Finally, only couples in their first marriage were kept in this study. According to Heckert et al. (1998), the propensity of divorce of couples in their second or third marriage is higher than couples who have been married only once. Therefore, it made no sense to treat these different types of marriages in the same fashion and include more than first marriages in my study. The final size of every five-year cross-year/ family files is presented below:

Table 5

Size of Every Five-Year File

File	Size
1968-1972	1323.02
1973-1977	1641.02
1978-1982	1810.42
1983-1987	1845.40
1988-1992	1918.18
1993-1997	1453.39

Note: The sample sizes are weighted to adjust for differential sampling proportions and no-response rates.

In order to build the following graphs describing the income and income ratio trends from 1968 to 1997, the income and income ratio annual means from all five-year files were assembled together. The generated graphs, therefore, do not have a single N (as this is the general case with statistical graphs), but are instead a composite of six different sample sizes.

Income and Income Ratio Trends

As stated in the literature review, there are two main longitudinal studies on the income dynamics of husbands and wives that emerge from the literature review on marital dissolution. The first study was conducted by Oppenheimer (1994) and was based on the Current Population Survey (CPS). This study encompassed 26 years of data (1964 to 1990), and included information on young people's weekly earnings. The second study was carried out by Raley, Mattingly, and Bianchi (2006) and included 31 years of household income data (1970 to 2001). The latter study also utilized the income data available on the CPS. These studies and their findings are very relevant to my dissertation because their length of time is very similar to my timeframe (approximately three decades) and, as is the case with my dissertation, they are based on a nationally sample survey. Both PSID and CPS are nationally representative samples of American households that contain data on couples' employment characteristics and demographics. The similarity of the studies described above will allow me to replicate their income and income ratio trends and/or challenge their findings with my own data. The only caveat worth mentioning on Oppenheimer's study is the fact that the income information is on men and women, rather than on couples. Furthermore, Oppenheimer used weekly income data and an adjusted scale for the income variable (the y-axis does not start with zero, but with $200), which increased at least visually the weekly variation of the men's and women's income.

Figure 1 shows the average annual income of heads of households from 1968 to 19997. This is an average annual income adjusted to 1995 dollars; in other words, it is real income. The year 1995 was used as the base year for adjusting the nominal incomes for 1968 to 1997, since this year is close to the last year of my study.

The average real income of heads of households increased 37% from 1968 to 1997, from $37,000 to $50,500. By contrast, Raley et al. (2006) found an increase of 22% in the husband's income between 1970 and 2001, from $48,200 to $58,900. Raley et al.'s income data was adjusted to real dollars in the year 2000. In spite of the 15% difference between the studies, both studies showed an upward trend for the husband's income for the last three decades.

On the contrary, Oppenheimer (1994) found that the average real income for young men—especially for the ones with less education—substantially deteriorated since 1970. In short, Oppenheimer showed that between 1969 and 1989, the real mean weekly earnings for high school graduates out of school for one to three years dropped 32%. Furthermore, this decline in the men's average weekly income was accompanied by a sharp increase in income inequality between the different levels of education. The deterioration of the men's income lies at the heart of Oppenheimer's argument, which states that the decrease in men's income explains the upward trend of the income ratio (calculated as women's income divided by men's income) in the 1970s and 1980s.

As previously discussed in the literature review, Oppenheimer contended that much of the scholarly attention has focused on women's increased participation in the labor force and their subsequent increase in labor income as major contributors for the rise in the divorce rate was well as an increase in the delayed marriage, nonmarriage, and reduction in the fertility rate. On the other hand, the decrease in the men's income and its effect on the income ratio received only marginal attention. Nonetheless, my data and Raley et al's (2006) findings do not support the argument that, on average, the husband's real income had suffered a decline in the last three decades.

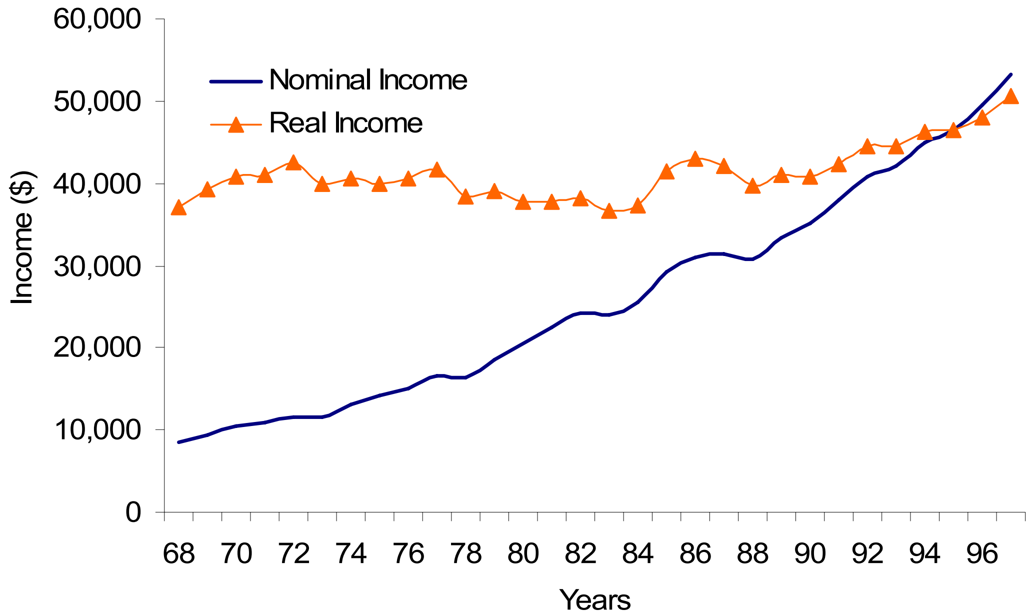

Figure 1. Average annual income of head of household, 1968-1997.

Note: Source: PSID. Nominal income was adjusted to 1995 dollars.

One of the most studied trends in the literature of marital dissolution is women's rising employment and income contribution in the past decades (see Nock, 2001; Oppenheimer, 1994; Ono, 1998; Raley, Mattingly & Bianchi, 2006; Rogers, 2004). As shown in Figure 2, the wife's annual real income increased an average of 240% from 1968 to 1997, from $5,500 to $18,600. Similarly, Raley et al. found in their study an increase of 200% in the wife's annual real income for the same period. One important finding in my study was a deceleration in the otherwise steady growth of the wife's annual real income in the last years of the 1990s (see Figure 2).

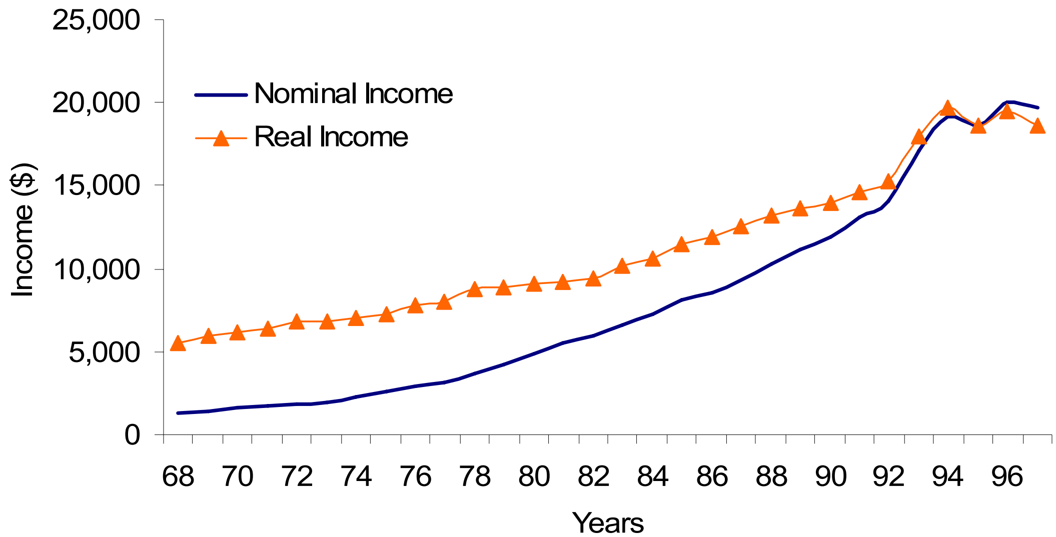

Figure 2. Average annual income of wife, 1968-1997.

Note: Source: PSID. Nominal income was adjusted to 1995 dollars.

Parallel to the increase of the wife's real income, my data revealed a marked decrease in the percentage of couples where the wife makes no income at all. Whereas a slight majority of wives (54%) made not income at all in 1968, the percentage of wives making no income had declined to 19% by 1997. On the other hand, the percentage of couples where the husband earns no income remained stagnant and negligible from 1968 to 1993, remaining close to 1%. After 1993, the percentage jumped to 5% and stayed at that level for the rest of the decade (see Figure 3).

This significant decrease in the percentage of couples with wives earning no income reflects an important income trend highlighted by Raley et al. (2006):

the consolidation of the dual income family in the contemporary United States. Raley et al. found that the vast majority of couples (70%) were dual providers in 2001, up from 41% in 1970. Dual earner couples include couples where the husband earns the majority of the household income, couples where both spouses are equal providers, and couples where the wife earns the majority of the household income.

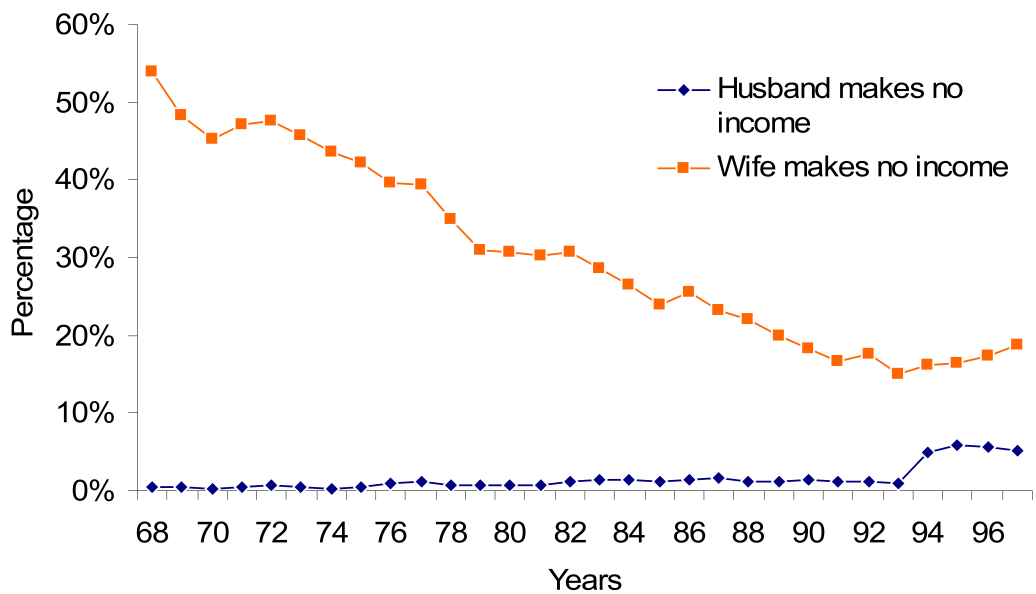

Figure 3. Husband and wife earn no income, 1968-1997.

Note: Source: PSID.

In regard to the prominence of the dual income family, Nock (2001) argued that among dual income families, the fastest growing group constituted the MEDS (marriages of equally dependent spouses where each spouse contributes 40%-59% of the family income). On the other hand, Moen and Sweet (2003) contended that a neotraditional type of couple has emerged to replace the traditional couple, where each spouse specialized in either domestic or market labor. In this new type of family, the husband remains as the main breadwinner and the wife does some market work, but adapts her career to accommodate her husband's opportunities at work.

As shown in Figure 4, my data supported both findings. Both MEDS and couples where the husband is the major provider reported the highest percentage increases (14% increase for both types of families from 1968 to 1997). Furthermore, the neotraditional couples where husbands earn the majority of the family income represent the largest group, accounting for 48% of all couples in 1997, up from 33% in 1968.

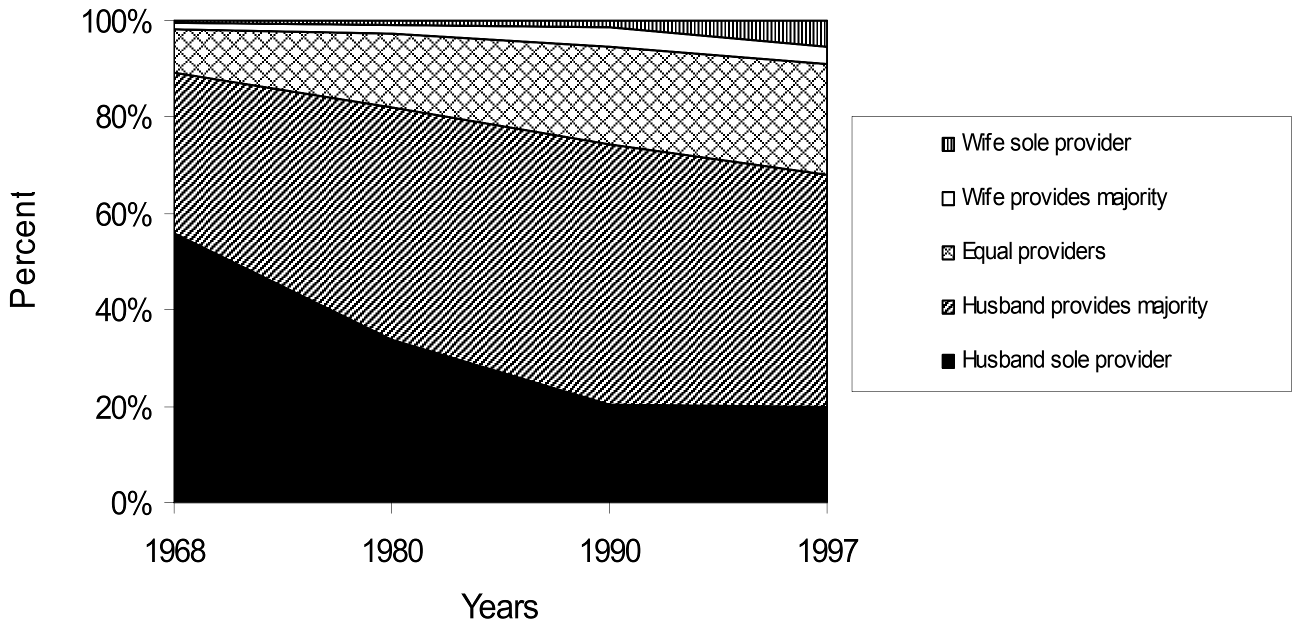

Figure 4. Percent distribution of households by couple's income contributions, 1968-1997.

Note: Source: PSID.

Figure 4 also shows that equal providers comprised 23% of total families in 1997 (up from 9% in 1968), and couples where the wife earns the majority accounted only for 4% in 1997. In short, Raley's et al. (2006) findings were replicated by my study. Both studies showed a predominance of dual income families (especially neotraditional couples and dual earners) and a decrease in the percentage of traditional households. Traditional households decreased from 56% in 1968 to 20% in 1997.

Among dual income couples between 1968 and 1997, the husbands' income increased 54% (from $31,500 to $48,600), whereas the wives' income almost doubled (from $12,300 to $22,800). In regard to the wife's income, households where the wife is the main breadwinner showed the most pronounced increase (a 99% increase between 1968 to 1997). On the other hand, the smallest increase in the wife's income during the last three decades (a 42% increase) occurred in the dual earner families.

Husbands' income tended to show a similar growth pattern compared to wife's income. From 1968 to 1997, the biggest increase in husbands' income occurred in the households where wives are the main breadwinner. Their income increased 130%, from $7,500 to $17,300. Furthermore, both husbands' and wives' incomes experienced a similar growth rate for dual earner households; 40% and 42%, respectively. This income information was taken from the five-year cross-year/family files.

Husband's and Wife's Income Ratio

From a methodological standpoint, I built an income ratio different from the one used by Raley et al. (2006). This income ratio has the husband's income as its numerator and the family household income (husband's income plus wife's income) as its denominator. By contrast, Raley's et al. income ratio is calculated by dividing the wife's income by the husband's income. The main reason for my methodological choice was parsimony; the range of my income ratio goes from zero to one, whereas the range of Raley's et al. income ratio is much larger. This ratio goes from zero to infinite (+ ∞). Furthermore, it is easier to build categories for modeling income instability or classify households based on the relative contribution of husband and wife to the household income if the denominator of the income ratio includes the total household income (see Figure 5). It is important to mention at this point that these income ratios do have different slopes, despite the fact that they show similar patterns.

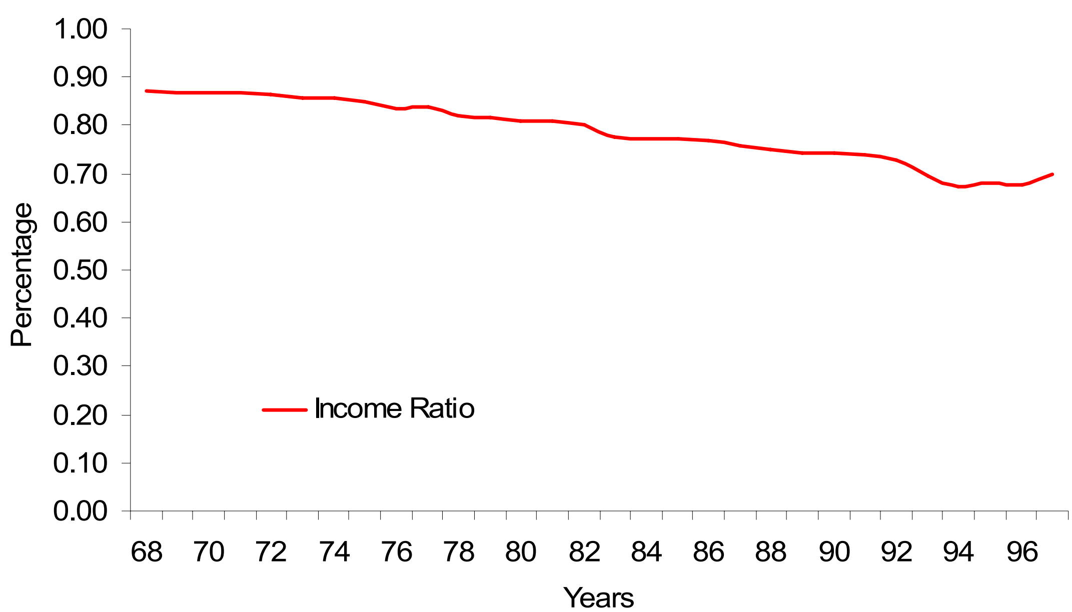

Figure 5. Husband's and wife's income ratio, 1968-1997.

Note: Source: PSID.

The algebraic sign of their slopes is explained by the particular way in which each of these ratios was constructed. In regard to my income ratio, it has a negative slope because the wife's income grew at a higher rate than the husband's income from 1968 to 1997.

As shown in Figure 5, the most striking characteristic of the income ratio of husbands and wives is actually how linear it appears to be. This income ratio started at 87% in 1968, and finished at 70% in 1997. Since it clearly depicts a linear pattern, I decided to build a simple Ordinal Least Squares (OLS) Regression to prove this assumption (see Figure 6). The income ratio of husband and wife was regressed against time in order to predict the income ratio for 2007. The OLS equation is:

$$\text{Expected income ratio} = 15.072 + (-0.0072)\,(\text{year}) \tag{14}$$

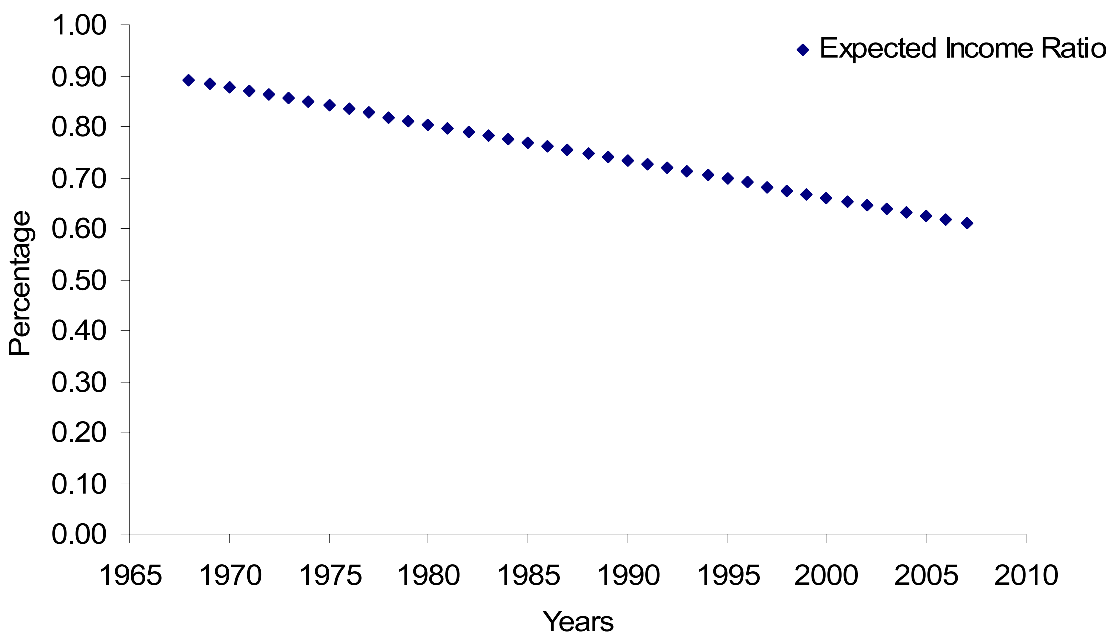

Figure 6. Expected income ratio, 1968-2007.

Note: Source: PSID.

The estimated R^2 is 97%, indicating that almost all the variation in the income ratio is explained by time. The predicted income ratio for 2007 is 61%; in other words, from 1968 to 2007, the husband's contribution to the household income is expected to drop 26%. In spite of the linear trend presented above, the annual standard deviation of the income ratio of husband and wife has experienced a steady increase from 1968 to 1997 (see Figure 7). The standard deviation went from 0.188 in 1968 to 0.253 in 1997. It is important to bear in mind that the range of this income ratio goes from zero to one. By 1997, therefore, the average variation of the income ratio approximated one-fourth of its range. According to Ritchey (2000), the standard deviation is a widely accepted proxy of variability or fluctuation in univariate or multivariate statistics. In this sense, my first hypothesis is confirmed. This hypothesis states that there is increasing fluctuation in the income ratio of husbands and wives in the United States during the last three decades.

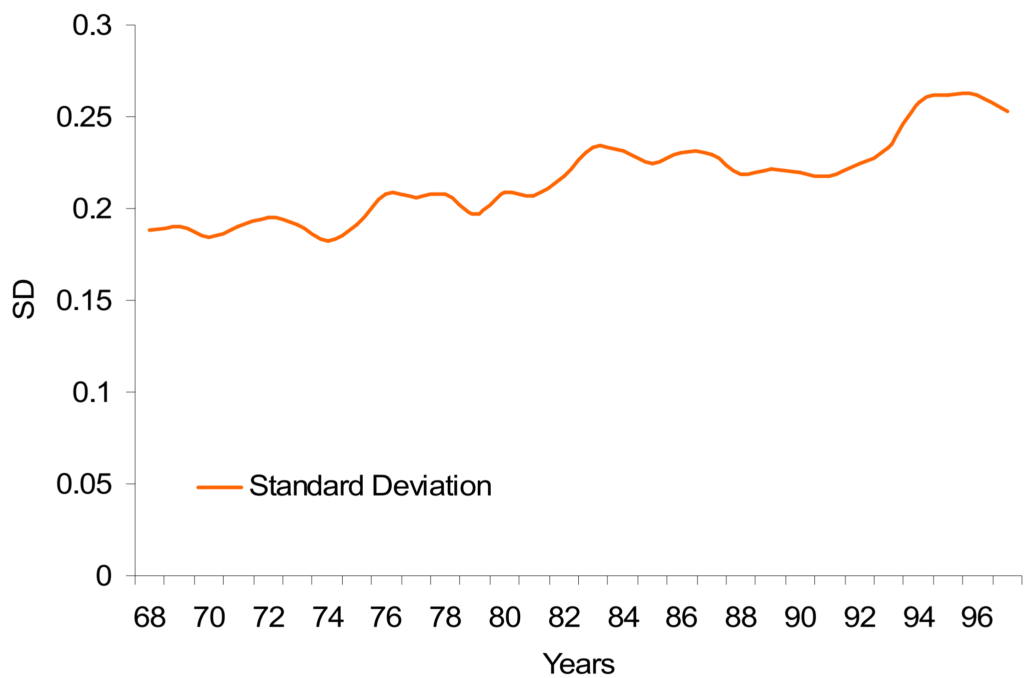

Figure 7. Standard deviation of husband's and wife's income ratio, 1968-1997.

Note: Source: PSID.

Logistic Regression

The tables showing the logistic regression results for marital disruption are presented below. The following six tables (one table for each time period) do not include the following covariates: age of wife at first marriage, years married, and cohabiting. The first two covariates were not collected every year during the relevant time frame of my dissertation (1968-1997). Furthermore, for those years where these variables were collected, the variables had too many missing cases. As for the variable “cohabiting”, the PSID code book indicated that relationship to head is the appropriate variable to identify legal wives from long term cohabitors. Nevertheless, the variable relationship to head was used to filter-off the family members other than the head of household in every five-year cross-year/family file. The cohabitors were, therefore, also excluded from the files. Due to this elimination process, it was no longer possible to distinguish the heads of households who are legally married from the heads who are cohabitors. In other words, all heads of households were kept in the study, but the possibility of differentiating husbands who are legally married from cohabitors was lost. The idea behind this weeding process was to eliminate the duplication of the head of household’s income data in the merged files.

First Logistic Regression Analysis (1968-1972)

Table 6 shows the logistic regression results for divorce and separation for 1968 to 1972. Categories two and three of age homogamy were collapsed in order to avoid zero cell count (the crosstabs between the divorce variable and age homogamy showed one cell with a zero value). A zero cell count distorts the

Logistic Regression Model and inflates the unstandarized beta coefficients and their standard errors. For the same reason, religion of wife and income instability were collapsed into Christian/Non-Christian and three levels of income instability, respectively. Race homogamy was not included in the model because the wife's race was not collected until 1985. The variable race of head was used instead. The lack of families with divorced heads of households from Latino, Filipino or other descendent limited this particular variable to only two categories: White and Black heads of households.

In order to test for multicollinearity, I ran the analysis once again using Ordinary Least Squares Regression (specifying the same dichotomous outcome and independent variables). Multicollinearity is an unacceptably high level of intecorrelations among the independent variables. According to David Nichols, Principal Support Statistician and Manager of Statistical Support for SPSS Inc. (http://socsci.colorado.edu/LAB/STATS/SPSS/), the collinearity diagnostics includes tolerance values, variance inflation factors (VIF), and condition indexes that list eigenvalues for the independent variables. Nichols contends that a tolerance value of less than 0.1 (or corresponding VIF of 10, since tolerance equals 1/VIF) indicates the presence of multicollinearity. Nevertheless, Nichols recommends using a more conservative "cutoff vale" (VIF = 3) for weaker models, like Logistic Regression.

The variance inflation factor (VIF) is a widely used test for multicollinearity because it shows directly how much the standard error of the estimation is inflated by multicollinearity. For the first five years of my study (1968-1972), two independent variables showed VIF values higher than three. The natural logarithm of the wife's income and the relative contribution of head of household to weekly labor work have VIF values of 3.3 and 3.6, respectively. Furthermore, the partial correlations among independent variables—both zero-order (Pearson) correlations and partial correlations controlling for other independent variables—showed a high correlation between these two variables. This partial correlations were -8.28 (zero-order correlation) and -.773 (partial correlation controlling for the other control variables included in the model). These partial correlations are high and confirm the suspicion of multicollinearity between the two independent variables mentioned before.

Additionally, these two variables have high values for the same eigenvalues, which also confirms the presence of multicollinearity. After carrying out the multicollinearity diagnostic, I decided to exclude the natural logarithm of the wife's income from my model. The other variable (the relative contribution of head of household to weekly labor work) had a stronger effect on the odds of divorce, so I decided to keep it in my study. After excluding the natural logarithm of the wife's income, the new multicollinearity diagnostic showed VIF values lower than two. Actually, the new VIF values range from 1.01 to 1.48, indicating that there is not vestige of multicollinearity issues among the independent variables in my model.

Table 6 shows that no resource dependencies, labor dependencies, and developmental dependencies were significantly associated with the odds of divorce. As is also shown in Table 6, the control variables were not associated with the odds of divorce. In regard to income ratio instability, my independent variable of interest, it showed neither statistical significance nor directionality in predicting the odds of marital disruption. In other words, increasing levels of income instability were not positively associated with the odds of divorce.

Table 6

Logistic Regression Results for Marital Disruption (1968-1972)

Variable	b	odds ratio
Resource dependencies		
Educational homogamy		
0-1 level difference	—	—
Husband 2+ levels higher	0.00	1.00
Wife 2+levels higher	-0.71	0.49
Labor dependencies		
Percent weekly housework by wife	-1.15	0.32
Percent weekly work hours by head	-1.91	0.15
Developmental dependencies		
Age youngest child		
Youngest child younger than 3 years	—	—
Youngest child between 3 and 17 years	0.35	1.43
No child in the household	0.30	1.35
Age homogamy		
Husband 1-3 years older	—	—
Husband 4 or 5 years older	-1.55	0.21
Husband 6 or more years older	-0.37	0.69
Wife 2 or more years older	0.96	2.60
Control variables		
Ln income-to-needs ratio	-0.69	0.50
Race of Head		
White	—	—
Black	0.46	1.58
Religion of wife		
Christian	—	—
Non-Christian	0.37	1.45

Table 6. Continued

Variable	b	odds ratio
Income Ratio Instability		
Stable pattern	—	—
First degree of instability	-2.28	0.10
Second degree of instability	0.43	1.54
Third degree of instability	-0.48	0.62

Note: n = 1,323
†*p* < .05, one-tailed. ††*p* < .001, one-tailed.

Second Logistic Regression Analysis (1973-1977)

Table 7 (1973-1977) did not include race homogamy since race of wife was not collected until 1985. I tried to merge race of wife for 1985 into the 1973-1977 cross-year/family file, but the resulting high number of missing cases forced me to exclude this variable from the analysis. Once again, race of head was used instead. Religion of wife was recoded into four categories: Protestant, Catholic, Jewish, and other or none. After conducting the multicollinearity diagnostics, the natural logarithm of the wife's income was excluded from the analysis. The resulting VIF values, after excluding this independent variable, ranged from 1.01 to 1.35, below the cut-off value of three.

Educational heterogamy was a significant predictor of marital disruption. Particularly, the odds of dissolution were 2.35 times as large for couples with husbands whose educational level is two levels higher than their wives as they were for couples with husbands who have the same educational level as their wives or only one level difference in their schooling. As was true in the previous time period (1968-1972), the relative contribution of the husband to the overall number of labor hours showed a negative association with the odds of dissolution. Nevertheless, this association was not statistically significant at the 0.05 level, one-tailed.

The only control variable that was a significant predictor of the odds of dissolution was religion of wife. Specifically, wives professing other religions or no religion had an odds ratio 5.7 times higher than Protestant wives did. As for income instability, my independent variable of interest, none of the categories showed a statistically significant association with the odds of divorce. During this time period (1973-1977), these categories showed a positive association with the odds of divorce, but these odds ratios (for the different categories of this particular variable) did not increase for higher levels of income ratio instability.

Table 7

Logistic Regression Results for Marital Disruption (1973-1977)

Variable	b	odds ratio
Resource dependencies		
Educational homogamy		
0-1 level difference	—	—
Husband 2 levels higher	0.86†	2.35
Husband 3+ levels higher	-0.78	0.46
Wife 2+ levels higher	0.31	1.36
Labor dependencies		
Percent weekly housework by wife	1.20	3.33
Percent weekly work hours by head	-0.85	0.43
Developmental dependencies		
Age youngest child		
Youngest child younger than 3 years	—	—
Youngest child between 3 and 17 years	0.33	1.39
No child in the household	0.33	1.39

Table 7. Continued

Variable	b	odds ratio
Age homogamy		
Husband 1-3 years older	—	—
Husband 4 or 5 years older	-0.03	0.98
Husband 6 or more years older	-0.19	0.83
Wife 2 or more years older	-0.12	0.89
Control variables		
Ln income-to-needs ratio	0.34	1.41
Race of Head		
White	—	—
Black	-0.39	0.68
Religion of wife		
Protestant	—	—
Catholic	0.16	1.17
Jewish	0.54	1.72
Other, none	1.74††	5.69
Income Ratio Instability		
Stable pattern	—	—
First degree of instability	0.43	1.54
Second degree of instability	0.05	1.05
Third degree of instability	0.17	1.18
Fourth degree of instability	0.07	1.07

Note: n = 1,641
$^{\dagger}p < .05$, one-tailed. $^{\dagger\dagger}p < .001$, one-tailed.

Third Logistic Regression Analysis (1978-1982)

The variable religion of wife was excluded from the logistic regression analysis for the period 1978 to1982. This particular variable was collected for 1976, and then from 1985 until the last wave in 1997. For this reason, religion of wife for 1985 was merged into the 1978-1992 cross year/family file. Nonetheless, the missing cases resulting from this merging were almost 10% of the sample size (173 cases), which made the Logistic Model unstable (inflated unstandarized beta coefficients and standard errors) due to the reduction in the sample size and the relatively small number of positive cases (divorced or separated couples) compared to the number of negative cases (married or cohabiting couples). For the previous time periods, religion of wife for 1976 was used without resulting in a significant number of missing cases. Furthermore, the natural logarithm of the wife's income was excluded from the model to avoid multicollinearity. The resulting VIF values, after excluding this variable, ranged from 1.01 to 1.28.

As shown in Table 8, the resource dependencies and the labor dependencies were not good predictors of the odds of divorce. On the other hand, both developmental dependencies—age of youngest child and age homogamy—showed a statistically significant association with the odds of divorce. For instance, the odds of divorce for couples with children between three and 17 years of age were 2.96 times as large as they were for couples with children younger than three years old. The odds ratio for families with no children in the household was slightly higher (3.5). Both associations were significant at the 0.05 level, one-tailed. In regard to age homogamy, couples where the husband is four to five years older than the wife showed a negative association with the odds of divorce. Each unit increment in age homogamy (e.g., from being in one age category to being in the next) decreased the odds of divorce by 86% [100*($e^{-1.97}$ - 1) = -86%]. This association was significant at the 0.05 level, one-tailed.

Table 8 shows that the first two degrees of income ratio instability, my independent variable of interest, were negatively associated with the odds of dissolution. Nonetheless, this association was not significant at the 0.05 level, one-tailed. On the other hand, the third and fourth degrees of income ratio instability were positively associated with the odds of divorce and were significant (p = 0.001 one-tailed and p = 0.01 one-tailed, respectively). These findings indicated that income ratio fluctuations are better predictors of the odds of divorce than stable income ratio patterns. Additionally, higher levels of income ratio instability are better predictors of the odds of divorce than lower levels of income ratio instability. For instance, the odds ratio for couples with the third level of income instability was 4.7. In the same vein, the odds of divorce for couples with the highest level of income instability (fourth level) were 5.0 times as large as they were for couples showing a stable income ratio pattern. The rationale behind using a one-tailed test is that I predicted directionality in the hypothesis testing of the beta coefficients for the Logistic Regression Model. For instance, I expected the beta coefficients of the different categories of income ratio instability to be significantly different than zero and positive (H_0: beta coefficient > 0), since I predicted a positive association between income ratio instability and the odds of divorce.

Table 8

Logistic Regression Results for Marital Disruption (1978-1982)

Variable	b	odds ratio
Resource dependencies		
Educational homogamy		
0-1 level difference	—	—
Husband 2 levels higher	-0.91	0.40
Husband 3+ levels higher	-3.39	0.03
Wife 2+ levels higher	-3.30	0.04

Table 8. Continued

Variable	b	odds ratio
Labor dependencies		
Percent weekly housework by wife	-0.41	0.66
Percent weekly work hours by head	-0.42	0.66
Developmental dependencies		
Age youngest child		
Youngest child younger than 3 years	—	—
Youngest child between 3 and 17 years	1.08†	2.96
No child in the household	1.25†	3.50
Age homogamy		
Husband 1-3 years older	—	—
Husband 4 or 5 years older	-1.97†	0.14
Husband 6 or more years older	0.13	1.14
Wife 2 or more years older	-0.13	0.88
Control variables		
Ln income-to-needs ratio	0.57	1.78
Race of Head		
White	—	—
Black	-0.63	0.53
Hispanic, other	-0.90	0.41
Income Ratio Instability		
Stable pattern	—	—
First degree of instability	-0.65	0.52
Second degree of instability	-0.15	0.86
Third degree of instability	1.54††	4.67
Fourth degree of instability	1.61†	5.01

Note: n = 1,810
†p < .05, one-tailed. ††p < .001, one-tailed.

Fourth Logistic Regression Analysis (1983-1987)

For the period 1983 to1987, religion of wife was included in the analysis and recoded into Christian, non-Christian, and atheist, agnostic or no religion in order to avoid zero cell count (see Table 9). For the same reason, the third and fourth categories of income ratio instability were also collapsed. As for race homogamy, this is the first time that this construct was included in the Logistic Regression Model since race of wife is available in the PSID dataset from 1985 to 1997. Nevertheless, only two categories were created (husband and wife are both White, and husband and wife are both Black) because there were no divorced or separated interracial couples in this five-year cross-year/family file. The natural logarithm of the wife's income was excluded from the model to avoid multicollinearity. The VIF values, after excluding this variable from the model, ranged from 1.02 to 1.30.

In regard to the resource dependencies, families where husbands are two educational levels higher than wives showed a positive association with the odds of divorce. This association was significant ($p = 0.04$, one-tailed). As for the control variables, the natural logarithm of income-to-needs ratio was a significant predictor of the odds of divorce ($p = 0.01$, one-tailed). Its odds ratio was 0.63, indicating a negative association with the odds of divorce. Religion of wife was also a strong predictor of the odds of divorce. In particular, couples where the wife is non-Christian and couples where the wife is atheist, agnostic or profess no religion were strongly correlated with the odds of divorce. Their respective odds ratios were 4.3 ($p = 0.01$, one-tailed) and 5.1 ($p = 0.001$, one-tailed). The reference category for religion of wife was Protestant wives.

The income ratio instability showed the same behavior as in the previous time period (1978-1982). Families with the highest level of income ratio instability (levels three and four collapsed) showed a positive association with the odds of divorce (odds ratio = 2.58), whereas families with the lowest level of income ratio instability were actually negatively associated with the odds of divorce (odds ratio = 0.83). The reference category was the stable income ratio pattern. Furthermore, the highest level of income ratio instability was a significant predictor of the odds of divorce (p = 0.005, one-tailed).

Table 9

Logistic Regression Results for Marital Disruption (1983-1987)

Variable	b	odds ratio
Resource dependencies		
Educational homogamy		
0-1 level difference	—	—
Husband 2 levels higher	$0.67^{\dagger}$	1.95
Husband 3+ levels higher	0.10	1.11
Wife 2+ levels higher	-0.02	0.98
Difference in husband-wife health status	-0.16	0.86
Labor dependencies		
Percent weekly housework by wife	0.44	1.56
Percent weekly work hours by head	0.04	1.04
Developmental dependencies		
Age youngest child		
Youngest child younger than 3 years	—	—
Youngest child between 3 and 17 years	0.47	1.60
No child in the household	0.77	2.16
Age homogamy		
Husband 1-3 years older	—	—
Husband 4 or 5 years older	0.23	1.26
Husband 6 or more years older	0.21	1.23
Wife 2 or more years older	-1.38	0.25
Control variables		
Ln income-to-needs ratio	$-0.46^{\dagger}$	0.63
Race homogamy		
Husband and wife both White	—	—
Husband and wife both Black	0.69	1.98

Table 9. Continued

Variable	b	odds ratio
Religion of wife		
Christian	—	—
Non-Christian	1.45†	4.26
Atheist, agnostic, other	1.62††	5.06
Husband lived with both parents as child	0.09	1.10
Income Ratio Instability		
Stable pattern	—	—
First degree of instability	-0.18	0.83
Second degree of instability	0.14	1.15
Third degree of instability	0.95†	2.58

Note: n = 1,845
†$p < .05$, one-tailed. ††$p < .001$, one-tailed.

Fifth Logistic Regression Analysis (1988-1992)

Religion of wife, race homogamy, and income ratio fluctuation were collapsed in the same fashion for the time period 1988 to1992 as they were for the previous time frame (1983-1987). The only two additional changes in the data was the exclusion of the variable age of youngest child and the natural logarithm of the wife's income. Age of youngest child had a relatively large percentage of missing cases in this time period (10% of the sample size). As was the case in previous time periods, the natural logarithm of wife's income was excluded to avoid multicollinearity. The exclusion of the latter variable generated a maximum VIF value of 1.3, below the cut-off value of three.

One out of the two resource dependencies were significant predictors of the odds of divorce (see Table 10).The difference in perceived health status of husband and wife (as perceived by the husband) was negatively associated with the odds of divorce. Each unit increment in the perceived difference in the health status of husband and wife decreased the odds of divorce by 41.9% [100*($e^{-0.52}$ - 1) = -41.9%].

In regard to the control variables, the income-to-needs ratio showed a significant association with the odds of divorce. Each one percent increase in this ratio represented a decrease of 42% in the odds of divorce [100*($e^{-0.53}$ - 1) = -42%]. Additionally, the odds of divorce for Black couples were 3.2 times as large as they were for White couples. This association was also statistically significant ($p = 0.001$, one-tailed). In the same vein, couples where wives are atheist, agnostic, or profess no religion had an odds ratio of 2.7, indicating that their odds of divorce were 2.7 times higher than the odds of divorce for families with Protestant wives. This association was statistically significant ($p = 0.01$, one-tailed).

As for income ratio instability, the association with the odds of divorce was not significant. Nevertheless, the direction of the association remained the same; in other words, higher levels of income ratio instability were positively associated with the odds of divorce, whereas lower levels of income ratio instability showed a negative association with the odds of divorce.

Table 10

Logistic Regression Results for Marital Disruption (1988-1992)

Variable	b	odds ratio
Resource dependencies		
Educational homogamy		
0-1 level difference	—	—
Husband 2 levels higher	0.10	1.10
Husband 3+ levels higher	0.15	1.16
Wife 2+ levels higher	0.58	1.79
Difference in husband-wife health status	-0.52††	0.59
Labor dependencies		
Percent weekly housework by wife	0.43	1.54
Percent weekly work hours by head	-0.70	0.50
Developmental dependencies		
Age homogamy		
Husband 1-3 years older	—	—
Husband 4 or 5 years older	-0.61	0.54
Husband 6 or more years older	-0.95	0.39
Wife 2 or more years older	0.35	1.41
Control variables		
Ln income-to-needs ratio	-0.53†	0.59
Race homogamy		
Husband and wife both White	—	—
Husband and wife both Black	1.15††	3.15
Religion of wife		
Christian	—	—
Non-Christian	0.40	1.49
Atheist, agnostic, other	0.99†	2.69
Husband lived with both parents as child	0.16	1.17
Income Ratio Instability		
Stable pattern	—	—
First degree of instability	-0.11	0.90
Second degree of instability	-0.73	0.48
Third degree of instability	0.14	1.16

Note: n = 1,918
†p < .05, one-tailed. ††p < .001, one-tailed.

Sixth Logistic Regression Analysis (1993-1997)

For the last time period considered (1993-1997), educational homogamy was recoded using a different educational variable since the previous educational variable used for past time periods was not collected from 1993 to 1997. These new educational variable allowed the construction of a similar variable measuring educational homogamy; however, the differences were not in educational levels, but in years of education. Race homogamy and age homogamy shared the same categories as they did in the previous time period, 1988-1992. Furthermore, income ratio instability had four levels of income ratio variation for the current time frame. There was no need to collapse categories for this variable since the crosstabs between income ratio instability and the divorce variable had no zero cell count. For this time period, the natural logarithm of the wife's income was excluded from the analysis to avoid multicollinearity. As was the case in the previous time periods, the highest VIF value for the independent variables in the multicollinearity diagnostics remained below three—the cut-off value to assess the presence of multicollinearity issues in the Logistic Regression Model.

As shown in Table 11, educational homogamy (built with the new educational variables) showed a statistically significant association with the odds of divorce. For instance, the odds of divorce for couples with husbands who are two years of education higher than their wives were 3 times higher than they were for couples with the same number of years of education or one year difference in their schooling. Only one of the developmental dependencies was a significant predictor of the odds of divorce. This was the case of age homogamy.

The odds of divorce for couples where wives were two or more years older than their husbands were 2.3 times higher than they were for couples where husbands and wives have the same age or one year difference. In regard to the control variables, the income-to-needs ratio was the only predictor of the odds of divorce. A one percent increase in the income to needs ratio decreased the odds of divorce by 41% [100*($e^{-0.54}$ - 1) = -41%].

As for the independent variable of interest, the highest level of the income ratio instability was a significant predictor of divorce for the last time period considered (1993-1997). This association was significant at the 0.05 level, one-tailed. Furthermore, the direction of the association actually reversed for this time frame; in other words, higher levels of income ratio instability showed a negative association with the odds of divorce (odds ratio = 0.26). These results contradicted the directionality and power of the association between income ratio instability and the likelihood of divorce stated in hypotheses two and three.

Table 11

Logistic Regression Results for Marital Disruption (1993-1997)

Variable	b	odds ratio
Resource dependencies		
Educational homogamy		
0-1 level difference	—	—
Husband 2 years higher	1.11†	3.04
Husband 3+ years higher	0.39	1.48
Wife 2+ years higher	-0.16	0.86
Difference in husband-wife health status	0.15	1.16

Table 11. Continued

Variable	b	odds ratio
Labor dependencies		
Percent weekly housework by wife	-0.70	0.50
Percent weekly work hours by head	-0.02	0.98
Developmental dependencies		
Age youngest child		
Youngest child younger than 3 years	—	—
Youngest child between 3 and 17 years	-0.06	0.95
No child in the household	-0.69	0.50
Age homogamy		
Husband 1-3 years older	—	—
Husband 4 or 5 years older	0.50	1.66
Husband 6 or more years older	0.23	1.26
Wife 2 or more years older	0.82†	2.26
Control variables		
Ln income-to-needs ratio	-0.54††	0.58
Race homogamy		
Husband and wife both White	—	—
Husband and wife both Black	0.17	1.18
Religion of wife		
Christian	—	—
Non-Christian	0.96	2.62
Atheist, agnostic, other	-0.51	0.60
Husband lived with both parents as child	0.63	1.87
Income Ratio Instability		
Stable pattern	—	—
First degree of instability	0.00	1.00
Second degree of instability	-0.07	0.93
Third degree of instability	-0.86	0.42
Fourth degree of instability	-1.34†	0.26

Note: n = 1,453
†*p* < .05, one-tailed. ††*p* < .001, one-tailed.

Summary of Logistic Regression Results for Marital Dissolution (1968-1997)

Hypothesis one states that there is increasing fluctuation in the income ratio of husbands and wives in the United States during the last three decades.

Figure 7 showed that the standard deviation of the income ratio variation of husbands and wives has consistently increased during the last thirty years. This finding confirms hypothesis one. Another important finding that also corroborates hypothesis one is the increasing percentage of couples who experienced higher levels of income ratio instability during the last three decades. For example, the percentage of families with higher levels of income ratio instability (levels three and four combined) was 8.53% in the first five-year period (1968-1972). This percentage increased to 12.6% for 1983-1987. Finally, during the last 5-year period studied (1993-1997), this percentage rose to 20.7%. In other words, not only has the instability of the income ratio of husbands and wives experienced a steady increase from 1968 to 1997, but the percentage of couples with higher levels of income ratio instability has also increased. Roughly one-fifth of the couples in the last decade were exposed to increasingly higher levels of variation in the relative contribution of husbands and wives to household income.

In regard to hypothesis two, this hypothesis states that income ratio instability is a stressor of marital life and is a better predictor of divorce than stable patterns in the couple's income ratio. As for hypothesis three, my final hypothesis, it states that couples showing a higher degree of income ratio instability are at a higher risk of divorce than couples with lower levels of income instability. As shown in Table 12, hypotheses two and three were supported for 1978-1992 and 1983-1987. Both hypotheses were not supported for the first two time periods (1968-1972 and 1973-1997). Hypotheses two and three were also not supported for 1988-1992. Nevertheless, the findings for the last time period

(1993-1997) actually contradicted hypotheses two and three. For 1993-1997, the association between higher levels of income ratio instability and the odds of divorce was negative, indicating that higher levels of income ratio fluctuation actually decrease the odds of marital dissolution. In the next chapter of this dissertation, I will try to explain in further detail the findings on income ratio instability, my independent variable of interest.

None of the dependencies or control variables showed statistically significant results for all six time periods being analyzed. However, three variables showed identifiable patterns throughout 1968 to 1997. For instance, education homogamy was positively associated wit the odds of divorce (husband is two educational levels higher than wife). On the other hand, the natural logarithm of income-to-needs ratio was negatively associated with the odds of divorce, and, finally, religion of wife was negatively associated with the odds of divorce, particularly the category that includes atheist, agnostic, and other religions.

Table 12

Summary of Logistic Regression Results for Marital Disruption (1968-1997)

Variable	Year					
	1968-1972	1973-1977	1978-1982	1983-1987	1988-1992	1993-1997
Educational homogamy	non-sig.	sig. (+)	non-sig.	sig. (+)	non-sig.	sig. (+)
Health status	—	—	—	non-sig.	sig. (-)	non-sig.
Percent weekly housework by wife	non-sig.	non-sig.	non-sig.	non-sig.	non-sig.	non-sig.
Percent weekly work hours by head	non-sig.	non-sig.	non-sig.	non-sig.	non-sig.	non-sig.
Age youngest child	non-sig.	non-sig.	sig. (+)	non-sig.	—	non-sig.
Age homogamy	non-sig.	non-sig.	sig. (-)	non-sig.	non-sig.	sig. (+)
Ln income-to-needs ratio	non-sig.	non-sig.	non-sig.	sig. (-)	sig. (-)	sig. (-)
Race	non-sig.	non-sig.	non-sig.	non-sig.	sig. (+)	non-sig.
Religion	non-sig.	sig. (+)	—	sig. (+)	sig. (+)	non-sig.
Income Ratio Instability	non-sig.	non-sig.	sig. (+)	sig. (+)	non-sig.	sig. (-)

Note: significance level is one-tailed.

CHAPTER VI

SUMMARY, CONCLUSIONS, RECOMMENDATIONS

Summary and Conclusions

The present study documented the occurrence of instability in the income ratio of husbands and wives from 1968 to 1997 in the United States. Based on the literature review on divorce and separation, this is the first time that such phenomenon—income ratio instability—is modeled in a longitudinal analysis. The vast majority of studies in the literature of marital dissolution address the association between the increasing contribution of women to the household income and divorce rate. Nevertheless, for the past three decades, the divorce rate has shown a curvilinear trend. According to the National Center for Health Statistics, the divorce rate has experienced curvilinear growth curve, growing fast in the 1960s and 1970s, and peaking in 1981, with a growth rate of 5.3 divorces per 1,000 people. Since 1981, this growth rate dropped to 3.6 divorces per 1,000 people in 2000. This is the lowest divorce rate since 1970 (http://www.cdc.gov/nchs/).

On the other hand, the women's participation in the labor market and their contribution to the household income have steadily increased since the 1960s. Despite the fact that the husband's income has also increased during this time period, the women's labor income has increased at a higher rate. This phenomenon is reflected by the decreasing income ratio of husbands and wives for 1968 to 1997, calculated as husband's income divided by the total household income. While this income ratio has declined during this time period, its standard deviation has steadily increased, as shown in Figure 7. This steady increase of the standard deviation confirmed hypothesis one, which states that there is increasing fluctuation in the income ratio of husbands and wives in the United States during the last three decades.

In regard to the association between the income ratio instability and the odds of divorce, I found statistically significant results for the late 1970s and early 1980s, confirming hypotheses two and three for these years. For the early 1970s and late 1980s, nonetheless, the association between income ratio instability and the odds of divorce was not significant. On the contrary, for the 1990s, this association was reversed, contradicting hypotheses two and three. In other words, during the 1990s, higher levels of income ratio instability were negatively correlated with the odds of divorce.

In spite of these contradicting results, I argue that the economic cycles could provide a rationale for explaining the change in direction of the association between income ratio fluctuation and the odds of divorce. As stated previously, the income ratio instability was negatively associated with the odds of divorce in the late 1970s and the 1980s in the United States. This timeframe coincided with the Reagan administration and the worst economic recession since the Great Depression.

According to Bureau of Statistics of the U.S. Department of Labor (www.bls.gov/), the unemployment rate in the United States rose from 6.1% in 1970 to 10.8% in 1982. By 1997, the unemployment rate dropped to 4.7%. The inflation rate (measured as the rate of change of the consumer price index) increased from 4.8% in 1970 to 11.2% in 1980. By 1990, the inflation rate dropped to 5.4%; by 1997, it dropped even further to 2.3%. Economic growth (measured by the GDP growth rate) also experienced an important change, from 0.2% in 1970 to -1.9% in 1982. By 1997, this growth rate grew to 4.5%. In light of this economic data, I argue that there could be an influence of various macroeconomic variables (unemployment rate, economic growth rate, and inflation) on the impact of income ratio instability on the odds of divorce. When inflation levels and the unemployment rate were high, the income ratio of husbands and wives was negatively associated with the odds of divorce. By contrast, when the United States enjoyed economic growth with low inflation and low unemployment, this relationship was non-significant and even reversed (from a positive association to a negative association), as shown in Table 11. Specifically, in the 1990s when the United States experienced an unprecedented period of economic growth and prosperity, higher levels of income ratio instability were actually negatively associated with the odds of divorce, indicating that possibly the instability of the income ratio of husbands and wives might constitute a stressor of divorce only when couples experience adverse economic conditions like economic recession. In the same vein, this fluctuation of the income ratio of husbands and wives became normative and thereby less of a stressor of marital dissolution in periods of economic growth, low inflation, and low unemployment rate.

With respect to the control variables and dependencies, some covariates showed distinctive patterns in this 30-year study. For example, age heterogamy was a significant predictor of the odds of divorce. Husbands with two more educational levels than their wives were more prone to divorce than husbands with the same educational level than their wives or with one level difference. Religion of wife was also an important predictor of the odds of marital disruption, despite the fact that this variable was not included in all five-year periods and was recoded somewhat differently throughout the length of this study to avoid zero cell count. As compared to families with Protestant wives, the category representing couples with agnostic, atheist or wives professing no religion was highly significant and showed a negative association with the odds of divorce. In regard to socioeconomic status, the income to needs ratio was negatively associated with the odds of divorce, perhaps indicating that higher levels of socioeconomic status are a deterrent of divorce compared to lower levels of socioeconomic status, controlling for other economic variables. As for the rest of the covariates, none of them showed a distinguishable pattern throughout this longitudinal study.

As for the limitations and shortcomings of this longitudinal study, the main limitation constituted the relatively small base rate of the dependent variable (marital status). This base rate (divorced cases/total cases) was reduced even further due to the model design. For instance, the conceptual model required the modeling of income ratio instability for at least five years in order to assess its impact on the odds of divorce in year No. 6. This implied that the number of divorced couples was reduced even further because the divorced couples were filtered-off for the first five years of every five-year file. The divorced couples were kept only for the last year (year No. 6) of every time period included in my study. The end result of this data reduction process was a base rate of 1% for 1968-1972. This base rate remained relatively small (4%) for the last time period studied (1993-1997). With a very small base rate, there is the possibility that the results of a Logistic Regression Model could be significant even though this model might be capturing only a random association. Furthermore, this small base rate of the divorce variable generated unstable results, especially with categorical covariates that had several categories. In these instances, the divorced cases had to be spread thin among the different categories, sometimes producing categories with no divorced cases at all. For this reason, several categorical variables had to be recoded or eliminated from the Logistic Regression Model altogether, jeopardizing the consistency of the analysis throughout time.

In regard to the strengths of my study, the most solid rationale in favor of the robustness of the Logistic Regression Model lies in its design; this model was based on theory. This model was built in sequential blocks which included resource dependencies, labor dependencies, and control variables. As explained in chapters two and three, the inclusion of these covariates was based in previous empirical research and theoretical developments in marital dissolution. From a statistical standpoint, this meant that the different groups of covariates were entered in the model in a sequential fashion (forced entry of covariates in sequential blocks). On the contrary, a Logistic Regression Model built for exploratory analysis usually entails forward or backward conditional entry of variables using the stepwise method. In other words, the best model is determined by an algorithm that keeps the best predictors in the model and weeds out the covariates that do not meet the criteria (probability) for stepwise entry or removal. Therefore, the Logistic Regression Model based on exploratory analysis is driven by the data and not by sound theory. This is not the case with my Logistic Regression Model. The inclusion of the model covariates and the covariate of interest (income ratio instability) was based on theory, particularly Nock's Theory of Dependence (1995; 2001) and Oppenheimer's Collaborative Model (1994).

Implications for Literature Review

A thorough review of the literature on marital dissolution showed a lack of previous research that directly addressed the impact of the instability of the relative income contribution of husbands and wives on the odds of dissolution. There is ample research—albeit with contradicting and even opposing findings—on the increasing women's labor participation (and labor income) and its effect on marriage, childbearing, marital happiness, and marital dissolution. By the same token, the normativity of unstable income ratio patterns, especially in the last decade in the United States, is also a novel concept. In other words, there is no previous research that studied the process by which the fluctuation of the income ratio of husbands and wives became a norm in the contemporary United States. On the contrary, previous research suggested that wives' economic contribution to the household is now normative (see Spain & Bianchi, 1996; Qian & Preston, 1993). In this sense, my research constitutes a unique contribution to the body of knowledge in marital dissolution because this is the first study that modeled the fluctuation of the relative contribution of husbands and wives to the household income as a stressor of marital life. One shortcoming of my study is the fact that my findings cannot directly support any theory in marital dissolution, since the theories introduced in the Literature Review Chapter of my dissertation were primarily developed to explain the association between increasing women's labor income and divorce rate.

With regard to the theoretical models of marital dissolution, I would place the income ratio fluctuation and its impact on divorce as an extension of the Collaborative Model developed by Oppenheimer (1997). This model posits an economic collaboration of husband and wife where both spouses contribute to the household income as a survival mechanism to buffer the family against economic down cycles, illness or the death of a spouse. This collaboration allows for the exchange in the role of main breadwinner depending on which spouse has better economic prospects at a given point in time. In the extreme, this exchange becomes an erratic fluctuation with no identifiable pattern; in other words, income ratio fluctuation. I argue that when this exchange in the role as the main breadwinner becomes erratic, particularly during adverse economic conditions, the buffer mechanism runs amok and ceases to perform its main duty; safeguarding the household against external stressors that could jeopardize its very existence. Nevertheless, this rationale has a caveat. For instance, when families are confronted with adverse economic conditions, the instability of the income ratio of husbands and wives has a pernicious effect on divorce. On the contrary, if the economy is booming and conditions are stable, the erratic fluctuation of the income ratio of husbands and wives has a neutral or even a negative effect on the odds of divorce. This negative effect could be explained by the fact that in the absence of adverse economic conditions, income ratio instability could become normative in contemporary American society.

Implications for Future Research

A logical next step for my research on marital dissolution would be the inclusion of macroeconomic variables in the Logistic Regression Model to assess their effect on the odds of divorce. The PSID does not gather macroeconomic data; however, it is possible to merge census data to the PSID dataset, as Teachman and Crowder (2002) did in their research on multilevel models in family research. In order to allow the macroeconomic variables to vary throughout time, it will be necessary to link the different five-year periods, so these variables will change from one period to the next. Otherwise, if the analysis is carried out for every five-year period independently, these macroeconomic variables will assume a constant value for every couple in each five-year period. Furthermore, it is possible to conduct more focalized studies for a specific timeframe, using different socio-economic variables that the PSID dataset already includes to assess their impact on the odds of divorce. These focalized studies could be carried out before trying to merge census macroeconomic variables to the PSID dataset.

In regard to the algorithm that models the fluctuation of the income ratio, this is the first time that the Theory of Combinations has been used to model the variability of the relative contribution of husbands and wives to the household income in the literature of family dissolution. The main reason for developing this algorithm was the fact that linear and curvilinear patterns were not a good fit to capture all possible combinations that the fluctuation of the income ratio could assume. To make it more powerful, however, this algorithm could be based on the Theory of Permutations instead. This theory will increase the sensitivity of the algorithm to fluctuations of the income ratio, since it incorporates order and directionality. Nevertheless, this increase will be exponential, so it will be necessary to develop software to handle the increased number of permutations. With this added power, I argue that this algorithm could be possibly used in longitudinal studies, especially in time series analysis which model random fluctuations.

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APPENDIX A

Syntax for the Combinations Algorithm for the Second Category (0.25 =< RATIO < 0.50) for 1968-1972

```
******************(0.50 > ratio >=0.25) First Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.25 and ratio_68 <  0.50) and (ratio_69 < 0.25 or ratio_69 >=
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 >= 0.25 and ratio_71 < 0.50)  and (ratio_72 >= 0.25 and ratio_72 <
0.50)) income_instability = 2 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 < 0.25 or ratio_70 >= 0.50)
and (ratio_71 >= 0.25 and ratio_71 <0.50)  and (ratio_72 >= 0.25 and ratio_72
<0.50)) income_instability = 2 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 < 0.25 or ratio_71 >= 0.50)  and (ratio_72 >= 0.25 and ratio_72
<0.50)) income_instability = 2 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 >= 0.25 and ratio_71 <0.50)  and (ratio_72 < 0.25 or ratio_72 >=
0.50)) income_instability = 2 .
EXECUTE .

*****************(0.50> ratio>= 0.25) Second Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 < 0.25 or ratio_69 >=
0.50) and (ratio_70 < 0.25 or ratio_70 >= 0.50)
and (ratio_71 >= 0.25 and ratio_71 < 0.50)  and (ratio_72 >= 0.25 and ratio_72 <
0.50)) income_instability = 3 .
EXECUTE .

*************************************************
```

```
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 < 0.25 or ratio_71  >= 0.50)  and (ratio_72 <  0.25 or ratio_72 >=
0.50)) income_instability = 3 .
EXECUTE .

************************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 < 0.25 or ratio_69 >=
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 < 0.25 or ratio_71 >= 0.50)  and (ratio_72 >= 0.25 and ratio_72 <
0.50)) income_instability = 3 .
EXECUTE .

************************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 < 0.25 or ratio_70 >= 0.50)
and (ratio_71 >= 0.25 and ratio_71 < 0.50)  and (ratio_72 < 0.25 or ratio_72 >=
0.50)) income_instability = 3 .
EXECUTE .

***********************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 < 0.25 or ratio_70 >= 0.50)
and (ratio_71 < 0.25 or ratio_71 >= 0.50)  and (ratio_72 >= 0.25 and ratio_72 <
0.50)) income_instability = 3 .
EXECUTE .

***********************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 < 0.25 or ratio_69 >=
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 >= 0.25 and ratio_71 < 0.50)  and (ratio_72 < 0.25 or ratio_72 >=
0.50)) income_instability = 3 .
EXECUTE .

******************(0.50> ratio>=0.25) Third Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 < 0.25 or ratio_69 >=
0.50) and (ratio_70 < 0.25 or ratio_70 >= 0.50)
and (ratio_71 < 0.25 or ratio_71 >= 0.50)  and (ratio_72 >= 0.25 and ratio_72
<0.50)) income_instability = 4 .
EXECUTE .

************************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 < 0.25 or ratio_69 >=
0.50) and (ratio_70 < 0.25 or ratio_70 >= 0.50)
```

```
and (ratio_71 >= 0.25 and ratio_71  < 0.50)  and (ratio_72 <  0.25 or ratio_72 >=
0.50)) income_instability = 4 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 < 0.25 or ratio_69 >=
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 < 0.25 or ratio_71 >= 0.50)  and (ratio_72 < 0.25 or ratio_72 >=
0.50)) income_instability = 4 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 < 0.25 or ratio_70 >= 0.50)
and (ratio_71 < 0.25 or ratio_71 >= 0.50)  and (ratio_72 < 0.25 or ratio_72 >=
0.50)) income_instability = 4 .
EXECUTE .

*******************(0.50 > ratio >= 0.25) Fourth Degree of Instability [1968-1972]***

IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 < 0.25 or ratio_69 >=
0.50) and (ratio_70 < 0.25 or ratio_70 >= 0.50)
and (ratio_71 < 0.25 or ratio_71 >= 0.50)  and (ratio_72 < 0.25 or ratio_72 >=
0.50)) income_instability = 5 .
EXECUTE .

IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 >=0.50 and ratio_71 < 0.75)  and (ratio_72 >=0.50 and ratio_72 <
0.75)) income_instability = 1 .
EXECUTE .

IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 >= 0.75 and ratio_69 <=
1.00) and (ratio_70 >= 0.75 and ratio_70 <= 1.00)
and (ratio_71 >=0.75 and ratio_71 <= 1.00)  and (ratio_72 >= 0.75 and ratio_72
<= 1.00)) income_instability = 1 .
EXECUTE .

IF ((ratio_68 >= 0.25 and ratio_68 < 0.50) and (ratio_69 < 0.25 and ratio_69 >=
0) and (ratio_70 < 0.25 and ratio_70 >= 0)
and (ratio_71 < 0.25 and ratio_71 >= 0)  and (ratio_72 < 0.25 and ratio_72 >= 0))
income_instability = 1 .
EXECUTE .
```

APPENDIX B

Syntax for the Combinations Algorithm for the Third
Category (0.50 =< RATIO < 0.75) for 1968-1972

```
*******************(0.75> ratio>=0.50) First Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 < 0.50 or ratio_69 >=
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 >= 0.50 and ratio_71 < 0.75)  and (ratio_72 >= 0.50 and ratio_72 <
0.75)) income_instability = 2 .
EXECUTE .

**************************************************

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 < 0.50 or ratio_70 >= 0.75)
and (ratio_71 >= 0.50 and ratio_71 < 0.75)  and (ratio_72 >= 0.50 and ratio_72 <
0.75)) income_instability = 2 .
EXECUTE .

**************************************************

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 < 0.50 or ratio_71 >= 0.75)  and (ratio_72 >= 0.50 and ratio_72
<0.75)) income_instability = 2 .
EXECUTE .

**************************************************
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 >= 0.50 and ratio_71 <0.75)  and (ratio_72 < 0.50 or ratio_72 >=
0.75)) income_instability = 2 .
EXECUTE .

******************(0.75> ratio>= 0.50) Second Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 < 0.50 or ratio_69 >=
0.75) and (ratio_70 < 0.50 or ratio_70 >= 0.75)
and (ratio_71 >= 0.50 and ratio_71 < 0.75)  and (ratio_72 >= 0.50 and ratio_72 <
0.75)) income_instability = 3 .
EXECUTE .
```

```
*************************************************
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 < 0.50 or ratio_71  >= 0.75)  and (ratio_72 <  0.50 or ratio_72 >=
0.75)) income_instability = 3 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 < 0.50 or ratio_69 >=
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 < 0.50 or ratio_71 >= 0.75)  and (ratio_72 >= 0.50 and ratio_72
<0.75)) income_instability = 3 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 < 0.50 or ratio_70 >= 0.75)
and (ratio_71 >= 0.50 and ratio_71 < 0.75)  and (ratio_72 < 0.50 or ratio_72 >=
0.75)) income_instability = 3 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 < 0.50 or ratio_70 >= 0.75)
and (ratio_71 < 0.50 or ratio_71 >= 0.75)  and (ratio_72 >= 0.50 and ratio_72 <
0.75)) income_instability = 3 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 < 0.50 or ratio_69 >=
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 >= 0.50 and ratio_71 < 0.75)  and (ratio_72 < 0.50 or ratio_72 >=
0.75)) income_instability = 3 .
EXECUTE .

******************(0.75> ratio>= 0.50) Third Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 < 0.50 or ratio_69 >=
0.75) and (ratio_70 < 0.50 or ratio_70 >= 0.75)
and (ratio_71 < 0.50 or ratio_71 >= 0.75)  and (ratio_72 >= 0.50 and ratio_72 <
0.75)) income_instability = 4 .
EXECUTE .

*************************************************
```

```
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 < 0.50 or ratio_69 >=
0.75) and (ratio_70 < 0.50 or ratio_70 >= 0.75)
and (ratio_71 >= 0.50 and ratio_71  < 0.75)  and (ratio_72 <  0.50 or ratio_72 >=
0.75)) income_instability = 4 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 < 0.50 or ratio_69 >=
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 < 0.50 or ratio_71 >= 0.75)  and (ratio_72 < 0.50 or ratio_72
>=0.75)) income_instability = 4 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 < 0.50 or ratio_70 >= 0.75)
and (ratio_71 < 0.50 or ratio_71 >= 0.75)  and (ratio_72 < 0.50 or ratio_72 >=
0.75)) income_instability = 4 .
EXECUTE .

******************(0.75> ratio >= 0.50) Fourth Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 < 0.50 or ratio_69 >=
0.75) and (ratio_70 < 0.50 or ratio_70 >= 0.75)
and (ratio_71 < 0.50 or ratio_71 >= 0.75)  and (ratio_72 < 0.50 or ratio_72 >=
0.75)) income_instability = 5 .
EXECUTE .

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.75) and (ratio_70
>= 0.75)
and (ratio_71 >=0.75)  and (ratio_72 >=0.75)) income_instability = 1 .
EXECUTE .

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 >= 0.25 and ratio_71 < 0.50)  and (ratio_72 >= 0.25 and ratio_72 <
0.50)) income_instability = 1 .
EXECUTE .

IF ((ratio_68 >= 0.50 and ratio_68 < 0.75) and (ratio_69 >= 0.00 and ratio_69 <
0.25) and (ratio_70 >= 0.00 and ratio_70 < 0.25)
and (ratio_71 >= 0.00 and ratio_71 < 0.25)  and (ratio_72 >= 0.00 and ratio_72 <
0.25)) income_instability = 1 .
EXECUTE .
```

APPENDIX C

Syntax for the Combinations Algorithm for the Fourth Category (0.75 =< RATIO =< 1.00) for 1968-1972

```
******************(1.00 >= ratio >= 0.75) First Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.75) and (ratio_70
>= 0.75 and ratio_70 <= 1.00)
and (ratio_71 >= 0.75 and ratio_71 <= 1.00)  and (ratio_72 >= 0.75 and ratio_72
<= 1.00)) income_instability = 2 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.75 and ratio_69
<= 1.00) and (ratio_70 < 0.75)
and (ratio_71 >= 0.75 and ratio_71 <=1.00)  and (ratio_72 >= 0.75 and ratio_72
<=1.00)) income_instability = 2 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.75 and ratio_69
<= 1.00) and (ratio_70 >= 0.75 and ratio_70 <= 1.00)
and (ratio_71 < 0.75)  and (ratio_72 >= 0.75 and ratio_72 <=1.00))
income_instability = 2 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.75 and ratio_69
<= 1.00) and (ratio_70 >= 0.75 and ratio_70 <= 1.00)
and (ratio_71 >= 0.75 and ratio_71 <=1.00)  and (ratio_72 < 0.75))
income_instability = 2 .
EXECUTE .

***************(1.00>= ratio >= 0.75) Second Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.75) and (ratio_70 <
0.75) and (ratio_71 >= 0.75 and ratio_71 <=1.00)  and (ratio_72 >= 0.75 and
ratio_72 <=1.00)) income_instability = 3 .
EXECUTE .

*************************************************

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.75 and ratio_69
<= 1.00) and (ratio_70 >= 0.75 and ratio_70 <= 1.00)
```

```
and (ratio_71 < 0.75)  and (ratio_72 <  0.75)) income_instability = 3 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.75) and (ratio_70
>= 0.75 and ratio_70 <= 1.00)
and (ratio_71 < 0.75)  and (ratio_72 >= 0.75 and ratio_72 <= 1.00))
income_instability = 3 .
EXECUTE .

*************************************************
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.75 and ratio_69
<= 1.00) and (ratio_70 < 0.75)
and (ratio_71 >= 0.75 and ratio_71 <= 1.00)  and (ratio_72 < 0.75))
income_instability = 3 .
EXECUTE .

************************************************
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.75 and ratio_69
<= 1.00) and (ratio_70 < 0.75)
and (ratio_71 < 0.75)  and (ratio_72>= 0.75 and ratio_72 <= 1.00))
income_instability = 3 .
EXECUTE .

************************************************
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.75) and (ratio_70
>= 0.75 and ratio_70 <= 1.00)
and (ratio_71 >= 0.75 and ratio_71 <= 1.00)  and (ratio_72< 0.75))
income_instability = 3 .
EXECUTE .

******************(1.00>= ratio>=0.75) Third Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.75) and (ratio_70 <
0.75) and (ratio_71 < 0.75)  and (ratio_72 >= 0.75 and ratio_72 <=1.00))
income_instability = 4 .
EXECUTE .

*************************************************

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.75) and (ratio_70 <
0.75) and (ratio_71 >= 0.75 and ratio_71  <= 1.00)  and (ratio_72 <  0.75))
income_instability = 4 .
EXECUTE .

*************************************************
```

```
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.75) and (ratio_70
>= 0.75 and ratio_70 <= 1.00)
and (ratio_71 < 0.75)  and (ratio_72 < 0.75)) income_instability = 4 .
EXECUTE .

**************************************************
IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.75 and ratio_69
<= 1.00) and (ratio_70 < 0.75)
and (ratio_71 < 0.75)  and (ratio_72 < 0.75)) income_instability = 4 .
EXECUTE .

*****************(1.00>= ratio >= 0.75) Fourth Degree of Instability [1968-1972] ***

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.75) and (ratio_70 <
0.75) and (ratio_71 < 0.75)  and (ratio_72 < 0.75)) income_instability = 5 .
EXECUTE .

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 < 0.25 and ratio_69
>=0) and (ratio_70 < 0.25 and ratio_70 >=0)
and (ratio_71 < 0.25 and ratio_71 >= 0)  and (ratio_72 < 0.25 and ratio_72 >= 0))
income_instability = 1 .
EXECUTE .

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.25 and ratio_69 <
0.50) and (ratio_70 >= 0.25 and ratio_70 < 0.50)
and (ratio_71 >= 0.25 and ratio_71 <  0.50)  and (ratio_72 >= 0.25 and ratio_72 <
0.50)) income_instability = 1 .
EXECUTE .

IF ((ratio_68 >= 0.75 and ratio_68 <= 1.00) and (ratio_69 >= 0.50 and ratio_69 <
0.75) and (ratio_70 >= 0.50 and ratio_70 < 0.75)
and (ratio_71 >= 0.50 and ratio_71 < 0.75)  and (ratio_72 >= 0.50 and ratio_72 <
0.75)) income_instability = 1 .
EXECUTE .
```