

Analyzing the 2004–2011 KFS Multiply Imputed Data

Prepared By:
Joseph Farhat
Alicia Robb

December 2013

The
**Kauffman
Firm Survey**



Ewing Marion

KAUFFMAN

Foundation

The
Kauffman
Firm Survey

2004 2005 2006 2007 2008 2009 2010 2011



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1. Introduction

The purpose of this document is to provide instructions to the KFS users regarding the proper use of the KFS multiply imputed data to draw statistically valid inferences in their works. Also, it describes the general framework of the imputation process.¹

Since data editing is first done prior to imputation, this document describes the general framework for data editing first. Data editing is a process that includes procedures for detecting and correcting errors in data. Errors occur due to misunderstanding the answers/questions, or item values for one item contradict with another item (inconsistency) and incorrect flow through prescribed skip patterns.

Understanding the underlying structure of the KFS questionnaire helps to distinguish data missing due to item non-response or due to unit non-response. Item non-response occurs when certain questions in a survey are not answered by a respondent. Unit non-response takes place when a business cannot be contacted or refuses to participate in a survey.

Legitimate missing (hard missing) value occurs when a business is sold, merged, temporarily stopped operations, permanently out of businesses, due to unit non-response or due to skip logic.

The following table shows the possible type of missing values by business status and year; it also shows the number of legitimate missing (hard missing) values in each year:

Cross-Section – Wide format

Year	2004	2005	2006	2007	2008	2009	2010	2011	Missing values in year t
Refusal		561	743	825	816	743	776	676	Hard missing
Stopped operation or sold or merged in any of previous follow-ups			303	671	1,015	1,399	1,685	1,941	Hard missing
Out of Business		260	321	299	344	250	218	209	Hard missing
Merged Or Sold		43	47	45	40	36	38	40	Hard missing
Temporarily Stopped		66	124	98	58	41	45	30	Hard missing
Located : No data was collected				75	49	51	40	25	Hard missing
Complete	4,928	3,998	3,390	2,915	2,606	2,408	2,126	2,007	Soft missing/Hard missing ^a

¹ Data users who are interested in better understanding data imputation methods, its statistical properties, derivations and theoretical underpinnings of these methods, can see the references section for recommended readings.

Longitudinal – Wide format

Year	2004	2005	2006	2007	2008	2009	2010	2011	Missing values in year t
Stopped operation or sold or merged in any of previous follow-ups			303	586	810	1,048	1,212	1,365	Hard missing
Out of Business		260	247	188	213	141	133	114	Hard missing
Merged Or Sold		43	36	36	25	23	20	17	Hard missing
Temporarily Stopped		53	86	61	31	21	25	14	Hard missing
Located : No data was collected				65	30	31	16	13	Hard missing
Complete	3,140	2,784	2,468	2,204	2,031	1,876	1,734	1,617	Soft missing/Hard missing ^a

^a Hard missing: due to skip logic

Longitudinal – Long format

Status	n	Duration	Obs.
Permanently stopped operations in the first follow-up	260	1	260
Sold or Merged in first follow-up	43	1	43
Permanently stopped operations in second follow-up	247	2	494
Sold or Merged in second follow-up	36	2	72
Permanently stopped operations in third follow-up	188	3	564
Sold or Merged in third follow-up	36	3	108
Permanently stopped operations in fourth follow-up	213	4	852
Sold or Merged in fourth follow-up	25	4	100
Permanently stopped operations in fifth follow-up	141	5	705
Sold or Merged in fifth follow-up	23	5	115
Permanently stopped operations in sixth follow-up	133	6	798
Sold or Merged in sixth follow-up	20	6	120
Permanently stopped operations in seventh follow-up	114	7	798
Sold or Merged in seventh follow-up	17	7	119
Temporarily stopped operations in seventh follow-up	14	7	98
Responded to first follow-up to seventh follow-up	1,630	8	13,040
Total	3,140		18,286

To determined legitimate non-response, the KFS data has a variable - final_status_code - that allows us to determine if the business is still in operation (complete the survey), dropped out, permanently stopped operations, temporarily stopped operations, merged, or was sold. Based on the final_status_code variable, we created a new variable – class_f - for every follow-up; the class_f variable has the following values and labels:

Value	Label
0	Located : No data was collected (due to skip logic)
1	Dropout (unit non-response) during follow-up t.
2	Missing because the business closed, sold or merged in the previous follow-ups.
3	Permanently stopped operations during follow-up t.
4	Merged, or sold during follow-up t.
5	Temporarily stopped operations during follow-up t.
6	Survival business(complete the survey)during follow-up t.

The skip pattern in the KFS comes into two major types: question skip logic and a section skip logic. Question skip logic involves conditionally asking/skipping questions based upon responses to prior question(s). Meanwhile, section skip logic involves asking/skipping a whole section in the survey questionnaire, based upon responses to prior question(s).

The primary goal of understanding the skip patterns and the underlying structure of the questionnaire is to recognize non-applicable questions responses (hard missing or legitimate missing) and differentiate them from responses that are missing (soft missing), due to refusal or didn't know response. Having the missing values clearly defined (soft vs. hard missing) helps us to determine the correct number of observations for each variable; it also explains why the number of observations varying from variable to variable, correctly constructing aggregate variables, and correctly imputing soft missing data.

2. Logical Imputation (Data Editing)

Logical (or deductive) imputation refers to any method that uniquely identified the true value of the missing value with certainty from within the data set.

There are two major types of missing data in KFS: unit non-response and item non-response. Unit nonresponse occurs when a business refuses to participate in the survey. In the KFS, the unit nonresponses are dealt with through weighting adjustments; thus, it is not subject for logical imputation or any other kind of imputation. Meanwhile, item nonresponse occurs when certain questions in a survey are not answered by a respondent.

The single-cohort panel structure of the KFS offers many possibilities for logical

imputation. To better understand what a deductive imputation procedure does, **some examples** are discussed:

2.1 Section C: Business Characteristics

As of the first follow-up, the KFS questionnaire asks the respondent to confirm legal status of the business, and then the legal status of the business is recorded under the “c1z2_legal_status” variable. In the baseline survey legal status of the business is recorded under “b2a_legal_status_0”. If the respondent confirms the legal status to be the same as in the previous year, the legal status of the business is copied from the previous year. Meanwhile, if the respondent confirms that the legal status is not the same as the previous year the legal status, he was asked to provide the new legal status of the business.

These types of questions do not have missing values due to skip logic but it has missing values due to legitimate missing values (business is sold, merged, temporarily stopped operations or permanently out of businesses, etc.), as well as missing values due to item non-response.

In section C, the KFS questionnaire asks about the total number of employees excluding owner(s) who are paid employees of the business. As a result of the skip logic, data for “c6_num_ft_employees,” and “c7_num_pt_employees,” has to be recoded to zero if “c5_num_employees” is zero.

```
* Example
global suffix "_0 _1 _2 _3 _4 _5 _6 _7"
foreach fup in $suffix{
replace c6_num_ft_employees`fup`=0 if c5_num_employees`fup`==0
replace c7_num_pt_employees`fup`=0 if c5_num_employees`fup`==0

replace c5_num_employees`fup'  =.a if classf`fup`<6
replace c6_num_ft_employees`fup'=.a if classf`fup`<6
replace c7_num_pt_employees`fup'=.a if classf`fup`<6
}
```

2.2 Section D: Strategy and Innovation

All variables in section D should be recorded for legitimate missing values. An examination of the questions skip logics indicate that the following recoding is needed:

1. “d3_a_num_patent,” “d3_b_num_copyright,” and “d3_c_num_trademark,” need to be recoded to zero if the answers for “d3_a_have_patent,” “d3_b_have_copyright,” or

“d3_c_have_trademark,” is no, respectively.

2. “d4_a_lic_out_patent,” “d4_b_lic_out_copyright,” and “d4_c_lic_out_trademark,” need to be recoded to zero if the answer for “d3_a_have_patent,” “d3_b_have_copyright,” or “d3_c_have_trademark,” is no, respectively.

3. “d7_perc_sales_indiv,” “d7_perc_sales_bus,” and “d7_perc_sales_govt,” need to be recoded to zero if the answer for “d6_have_sales,” is no.

```
* Example
foreach fup in $suffix{
replace d3_a_have_patent`fup'          =.a if classf`fup'<6
replace d3_a_num_patent`fup'          =.a if classf`fup'<6
replace d4_a_lic_out_patent`fup'      =.a if classf`fup'<6
replace d5_a_lic_in_patent`fup'      =.a if classf`fup'<6
}
foreach fup in $suffix{
replace d3_a_num_patent`fup'          = 0 if d3_a_have_patent`fup' ==0
replace d4_a_lic_out_patent`fup'      = 0 if d3_a_have_patent`fup' ==0
}
```

2.3 Section E: Business Organization and Human Resource Benefits

All variables in section E should be re-coded for legitimate missing values. Section E has both question skip logic and section skip logic. The entire section was skipped for businesses that has one owner (c2_owners) and reported zero employees (c5_num_employees). Meanwhile, the part-time employee benefits questions were skipped for businesses that reported the number of part-time employees is zero.

```
* Example
foreach fup in $suffix{
gen skip_e`fup'=1 if c2_owners`fup'== 1 & c5_num_employees`fup'== 0
replace e1_a_num_human_res`fup'      =.a      if skip_e`fup'==1
replace e2a_ft_emp_bonus_plan`fup'   =.a      if skip_e`fup'==1
replace e2b_pt_emp_bonus_plan`fup'   =.a      if c7_num_pt_employees`fup' ==
0
replace e1_a_num_human_res`fup'      =.a      if classf`fup' <6
replace e2a_ft_emp_bonus_plan`fup'   =.a if classf`fup' <6
replace e2b_pt_emp_bonus_plan`fup'   =.a if classf`fup' <6
}
```

2.4 Section F: Business Finances

Section F deals with the major sources of financing, namely equity, debt and other financial information of the business. Since that the KFS collect data for up to 10 active-owner-operators, each owner was assigned a number. For all variables that are related to the active-owner-operators, the number prior to the "0, 1, 2, 3, 4, 5, 6, 7" suffixes

indicates the number assigned to the owner. For example, “f2_owner_amt_eq_invest_02_1,” refers the equity injection by owner number two in the first follow-up. While “f2_owner_amt_eq_invest_09_1,” refers the equity injections by owner number nine in the first follow-up. Unless indicated, the variables in this document are listed without a suffix, if the variable name is the same across all rounds.

In the baseline survey, the respondent was always owner number one. Since that the respondent could change from one follow-up to the next one, starting from the first follow-up the variable “respondent” contains the number of the owners who responded for the business in a particular follow-up.

While KFS collect data for up to 10 active-owner-operators, the number assigned to the owner can be more than 10. Since some owners who use to be active (non-active) in one follow-up could be non-active (active) in another, thus the number assigned to the owner can be more than 10.

Starting from the first follow-up and to identify active-owner-operators in each follow-up surveys, a variable called “owner-active-owner-number,” were created to ensure users could see which owner was still an active-owner-operator in the business:

For all the financial variables in the KFS, if the respondent did not provided the exact amount of the variable in dollars, the respondent was asked to provide a range of the amount instead. The range interval classes were standard across all the financial variables in the KFS. The interval classes are:

\$0	00
\$500 or less,	01
\$501 to \$1,000,	02
\$1,001 to \$3,000,	03
\$3,001 to \$5,000,	04
\$5,001 to \$10,000,	05
\$10,001 to \$25,000,	06
\$25,001 to \$100,000,	07
\$100,001 to \$1,000,000,	08
\$1,000,001 or more?	09
Don't Know"
Refused"

Based on the exact amount of the variable or the range of the amount provided by

the respondent, new variables were constructed for ease of analysis. The constructed variables represent the financial variables, in terms of range interval classes, by translating the exact amount into a range. To distinguish these variables from the range variables, the term “r” was included into the variables name.

2.4.1 Equity Injections by the Active-Owner-Operators

In every survey, the respondents were asked about their equity injections into the business in that year (indicator question), and the amount that was injected, if any. Starting from the first follow-up, respondents were asked to provide how much equity they injected into the business in all years.

For businesses that have more than one owner, equity injections by other active-owner-operators, up to nine of them, were collected through the respondents. The respondents were asked about the equity injections into the business by each of other active-owner-operators in that year (yearly inflow), and the amount that was injected, if any. Starting from the first follow-up, respondents were asked to provide how much equity each of other active-owner-operators injected, if they obtained equity financing during follow-up t, into the business in all years.

The amount of equity injections needs to be re-coded to zero, if the active-owner-operators states that he/they did not inject equity into the business in that follow-up.

Recoding hard missing values are required for two type of missing values. First, all variables in section F should be recorded for legitimate missing values. Second, the variables for non-active-owner-operator should be recoded to hard missing values.

Since that equity injection by other owners is not applicable for the businesses that reported having one active-owner-operator, the variables of equity injections for other owners needs to recode to hard missing values.

```
* Example
global owners_1_15 "01 02 03 04 05 06 07 08 09 10 11 12 13 14 15"

forvalues i = 0/7 {
  foreach ow in $owners_1_15 {
    replace f2_owner_eq_invest_`ow'`i'      =.a    if    owner_active_`ow'`i'
    !=1
  }
}
```

```

forvalues i = 0/7 {
  foreach ow in $owners_1_15 {
    replace f2_owner_amt_eq_invest_`ow'`i' =0 if
    f2_owner_eq_invest_`ow'`i'==0
  }
}

forvalues i = 0/7 {
  foreach ow in $owners_1_15 {
    replace f2_owner_eq_invest_`ow'`i' =.a if classf_`i'<6
    replace f2_owner_amt_eq_invest_`ow'`i' =.a if classf_`i'<6
  }
}

```

2.4.2 Equity Injections by Other Owners

In every survey, the respondents were asked if the business obtain equity financing from owners who are not actively involved in operating the business, non-operator-owners, and the amount that was obtained, if any. The balance of each source of funding that was used during follow-up t was collected in every follow-up survey. Data collections for equity financing obtained from non-operator-owners were at the aggregate level.

The amount of equity injections needs to be recoded to zero if the non-active-owner-operators state that he/they did not inject equity into the business in that follow-up.

Since that equity injection by other owners is not applicable for the businesses that reported the legal status being sole proprietorship, the variables for sole proprietorship needs to recode to hard missing values.

```

* Example
global List1 "spouse parents angels companies govt vent_cap other"

forvalues i = 0/7 {
  foreach name in $List1 {
    replace f3_eq_invest_`name'`i' =.a if clz2_legal_status_`i'==1
    replace f4_eq_amt_`name'`i' =.a if clz2_legal_status_`i'==1
    replace f4_eq_amt_`name'`i' = 0 if f3_eq_invest_`name'`i'==0
    replace f3_eq_invest_`name'`i' =.a if classf_`i'<6
    replace f4_eq_amt_`name'`i' =.a if classf_`i'<6
  }
}

```

2.4.3 Personal Debt Obtained by the Respondent

Respondents were asked about all types of personal debt that was obtained in their names on behalf of the business, and how much of this debt was obtained, if any, during follow-up t. In addition to the amount obtained every year for each type of personal debt, the amount owed for each type of personal debt used in follow-up t was collected.

The amount of personal debt needs to be recoded to zero, if the respondent states that he/she did not use that source of funding. Also, the number of personal debt used needs to be recoded to zero, if the respondent states that they did not use that source of funding.

```
* Example
forvalues i = 0/7 {
  replace f7b_pers_loan_bank_numused_`i' =0 if f7a_pers_loan_bank_`i' ==0
  replace f8c_pers_loan_bank_amt_`i'      =0 if f7a_pers_loan_bank_`i' ==0
  replace f7a_pers_loan_bank_`i'          =.a if classf_`i'<6
  replace f7b_pers_loan_bank_numused_`i' =.a if classf_`i'<6
}
```

2.4.4 Personal Debt Obtained by the Other Owners

For businesses that have more than one active-owner-operator, the respondents were asked to report all type of personal debt that was obtained by all other owners on behalf of the business, and how much was obtained, if any. Unlike equity financing by other owners, personal debt by other owners was collected at the aggregate level for active-owner-operators only. In addition to the amount of personal debt obtained by active-owner-operators in every year for each type of personal debt, the amount owed for each type of personal debt used in follow-up t was collected.

Since that personal debt obtained by the other owners is not applicable for the businesses that reported having one active-owner-operator, these variables for businesses that reported having one active-owner-operators need to be recoded to hard missing values.

The amount of personal debt obtained by the other owners needs to be recoded to zero, if the respondent states that they did not use that source of funding. Also, the number of personal debt used by the other owners needs to be recoded to zero, if the respondent states that they did not use that source of funding.

```

* Example
forvalues i = 0/7 {
replace f9a_pers_loan_bank_`i'      =.a if c4_numowners_confirm_`i'<2
replace f9b_pers_loan_bank_numused_`i'=.a if c4_numowners_confirm_`i'<2
replace f10c_pers_loan_bank_amt_`i'  =.a if c4_numowners_confirm_`i'<2
replace f10c_pers_loan_bank_amt_`i'  =0  if f9a_pers_loan_bank_`i' ==0
replace f9b_pers_loan_bank_numused_`i'=0  if f9a_pers_loan_bank_`i' ==0
replace f9a_pers_loan_bank_`i'      =.a if classf_`i'<6
replace f9b_pers_loan_bank_numused_`i'=.a if classf_`i'<6
replace f10c_pers_loan_bank_amt_`i'  =.a if classf_`i'<6
}

```

2.4.5 Debt Obtained by the Business

In addition to personal debt financing, the KFS collects data about different types of debt financing that were obtained in the name of the business during baseline and each follow-up survey.

The amount of debt obtained by the business needs to be recoded to zero, if the respondent states that the business did not use that source of funding. Also, the number of business debt used needs to be recoded to zero if the respondent states that the business did not use that source of funding.

```

* Example
forvalues i = 0/7 {
replace f11a_bus_loans_bank_`i'      =.a if classf_`i'<6
replace f12c_bus_loans_bank_amt_`i'  =.a if classf_`i'<6
replace f11b_bus_loans_bank_numused_`i'=.a if classf_`i'<6
replace f11b_bus_loans_bank_numused_`i'=0  if f11a_bus_loans_bank_`i'==0
replace f12c_bus_loans_bank_amt_`i'  =0  if f11a_bus_loans_bank_`i'==0
replace f11a_bus_loans_emp_`i'      =.a if c5_num_employees_`i'==0
replace f11a_bus_loans_owner_`i'    =.a if c2_owners_`i'==1
}

```

2.4.6 Other Financial Information

In addition to the sources of financing, the KFS collects much other financial information from the balance sheet and income statement, as well as financial information regarding the existence of R&D and rental or lease.

2.4.7 Section G: Work Behaviors and Demographics of Active-Owner-Operators

Information regarding work behaviors by active-owner-operators was collected in the baseline, as well as in every follow-up survey. Meanwhile demographics information was collected once. If the demographics information of an active-owner-operator was collected during follow-up t-1, then no demographics information will be collected during follow-up t. If the demographics information of an active-owner-

operator was missing in follow-up t-1, then we keep asking about this missing information in the following surveys until we have a valid response. During each follow-up, the work behaviors and demographics of newly active-owner-operators were collected.

For example, if the race information of an active-owner-operator was missing in follow-up t-1, then we keep asking about this missing information in the following surveys until we have a valid response. Thus, missing data for follow-up t-1 can be directly filled from other portions of an individual's record.

The work behaviors and demographics variables for non-active-owner-operator should be recoded to hard missing values.

For the race categories, questions respondents were allowed to report multiracial or mixed-race. Thus, there is a question for each race. Since it is more practical for analysis purposes to have one variable with race coded as categorical variable, we created a new race variable "g6_race_group," having the following codes:

- American Indian Or Alaska Native 01
- Native Hawaiian Or Other Pacific Islander 02
- Asian 03
- Black Or African American..... 04
- White 05
- Other Races Or Mixed Race..... 06

Owners reported multiracial or mixed-race were recorded as Other Races.

```
* Example
forvalues i = 0/7 {
  foreach ow in $owners_1_15 {
    replace gla_emp_owner`ow'`i'      =.a if owner_active`ow'`i'!=1
    replace gla_emp_owner`ow'`i'      =.a if classf`i'<6
  }
}
foreach ow in $owners_1_15{
/*Last observation carried backward */
replace      g4_age_owner`ow'`_0=g4_age_owner`ow'`_1-1      if
g4_age_owner`ow'`_0==.
replace      g4_age_owner`ow'`_0=g4_age_owner`ow'`_2-2      if
g4_age_owner`ow'`_0==.
replace      g4_age_owner`ow'`_0=g4_age_owner`ow'`_3-3      if
g4_age_owner`ow'`_0==.
replace      g4_age_owner`ow'`_0=g4_age_owner`ow'`_4-4      if
g4_age_owner`ow'`_0==.
replace      g4_age_owner`ow'`_0=g4_age_owner`ow'`_5-5      if
```

```

g4_age_owner_`ow'_0==.
replace      g4_age_owner_`ow'_0=g4_age_owner_`ow'_6-6      if
g4_age_owner_`ow'_0==.
replace g4_age_owner_`ow'_0=g4_age_owner_`ow'_7-7 if
g4_age_owner_`ow'_0==. }
foreach ow in $owners_1_15{
replace      g4_age_owner_`ow'_1      =g4_age_owner_`ow'_0+1      if
g4_age_owner_`ow'_1==.
replace      g4_age_owner_`ow'_2      =g4_age_owner_`ow'_0+2      if
g4_age_owner_`ow'_2==.
replace      g4_age_owner_`ow'_3      =g4_age_owner_`ow'_0+3      if
g4_age_owner_`ow'_3==.
replace      g4_age_owner_`ow'_4      =g4_age_owner_`ow'_0+4      if
g4_age_owner_`ow'_4==.
replace      g4_age_owner_`ow'_5      =g4_age_owner_`ow'_0+5      if
g4_age_owner_`ow'_5==.
replace      g4_age_owner_`ow'_6      =g4_age_owner_`ow'_0+6      if
g4_age_owner_`ow'_6==.
replace      g4_age_owner_`ow'_7      =g4_age_owner_`ow'_0+7      if
g4_age_owner_`ow'_7==.
}
forvalues i = 0/7 {
foreach ow in $owners_1_15 {
/* Recode legitimate missing values */
replace      g4_age_owner_`ow'_'i'=.a if owner_active_`ow'_'i'!=1
replace      g4_age_owner_`ow'_'i'=.a if classf_`i'<6
}
}

```

2.5 Questions Added / Dropped From the KFS Questionnaires during the Survey Period

In addition to the fixed core set of questions asked by all businesses in every follow-up survey, over the years some new questions were added to the survey questionnaires and some of these questions were dropped later on.

Appendix B summarizes all the questions that were added to KFS questionnaires during the survey period, as well as in which year the questions were dropped, if they were dropped.

3. Single imputation

3.1 Last observation carried forward (LOCF) and last observation carried backward (LOCB).

Both LOCF and LOCB methods can be used in longitudinal research designs, but they require the strong assumption of stability. LOCF takes into account the individual's previous observed value on a given variable. If an observation at a certain data collection wave is missing, the last observed value is then used as an estimate for

this missing observation.

A related method, last observation carried backward (LOCB), works according to the same approach, but imputes a newer observation in the case of a missing earlier observation of the same individual.

- LOCF was used to impute the legal status variable and business location.
- To determine the missing values for d1a_provide_service and d1b_provide_product variables, we use the NAICS description to determine if the business is operating under the services or manufacturing industries. For the observations that we couldn't determine if they provide a service or product, we use LOCF method of imputation.
- For the Longitudinal file, LOCF is used to fill in all the fixed core set of questions for businesses reported being temporarily stopped or located (no data was collected) ;LOCF implemented after the MI.

3.2 Internal consistency: using information from related observations

- For c2_owners: missing and zero values were replaced by total owners.
- The “c4_numowners_confirm,” was replaced by the sum of “owner-active,” if “c4_numowners_confirm,” is not equal to sum of the owner-active.
- Replace “c1z2_legal_status=7,” if “c1z2_legal_status=1,” and “c4_numowners_confirm_1>1.”

3.3 Other single imputations

- For d7_perc_sales_xxxx variables, if one variable has missing value we impute the missing value using: 100-sum (non-missing d7_perc_sales_xxxx).
- For f8xxx_line_y, f8xxx_bal_y, f8xxx_owed_y, f10xxx_line_y, f10xxx_bal_y, f10xxx_owed_y, f12xxx_line_y, f12xxx_bal_y, f12xxx_owed_y, , and f4_eq_amt_xxx_alllys the missing values set to zero if the business never use these sources of funding.

For example:

```
* Example
Replace f10d_pers_loan_fam_owed_2 =0 if f9a_pers_loan_fam_0 ==0 & ///
f9a_pers_loan_fam_1 ==0 & f9a_pers_loan_fam_2 ==0
```


4. Missing Data

The details of the percentage of missing values for each variable are provided in Appendix A.

The following table shows that for the fixed core set of questions (asked by all businesses in every survey) in about 90% of the variables the missing values are less than 5%, for 8% of the variables the missing values are within 5%-15%, and only about 2% have the missing values greater than 15%.

Count / Wave	0	1	2	3	4	5	6	7	All
Proportion of missings <= 0.05	88.71%	91.94%	91.94%	91.94%	87.10%	87.74%	88.71%	88.06%	89.52%
Proportion of missings 0.05 - 0.15	9.03%	8.06%	6.13%	3.23%	10.97%	10.32%	9.35%	10.00%	8.39%
Proportion of missings > 0.15	2.26%	0.00%	1.94%	4.84%	1.94%	1.94%	1.94%	1.94%	2.10%

The above classification is based on Harrell crude guidelines (2001).

5. The KFS multiply imputed data

Multiple imputations involve generating “m” substitute sets for the missing values, which allows for the uncertainty due to imputation to be reflected in the analysis (Rubin, 1978, 1987). The imputed values are ideally independent draws from the predictive distribution of the missing values conditional on the observed values. For the KFS multiply imputed data there are five completed data sets (m=5).

The multiple imputations for the KFS fixed core set of questions (asked by all businesses in every survey) were created using sequential regression multivariate imputation (SRMI) (Raghunathan et al., 2001), as implemented by the module `mi impute chained` in STATA software.

"... `mi imputes chained` fills in missing values in multiple variables iteratively by using chained equations, a sequence of univariate imputation methods with fully conditional specification (FCS) of prediction equations."

Mi imputes chained works as follows:

Let “Z” denote the fully-observed variables, and let X_1, X_2, X_k denote k variables with missing values, ordered by the amount missing, from least to most.

The imputation process for X_1, X_2, X_k proceeds in 10 iterations.

- In the first iteration: the regression of X_1 on Z is fitted, and the missing

values of X_1 are imputed (randomly from an approximate predictive distribution based on the fitted regression).

- Then the regression of X_2 on Z and X_1 (including the imputed values of X_1) is fitted, and the missing values of X_2 are imputed.
- and so on, until the regression of X_k on $Z, X_1, X_2, \dots, X_{k-1}$ is fitted, and the missing values of X_k are imputed.

In iterations 2 through 10:

- The regression of X_1 on Z, X_2, X_k is fitted, and the missing values of X_1 are imputed.
- Then the regression of X_2 on Z, X_1, X_3, X_k is fitted, and the missing values of X_2 are imputed.
- And so on, until the regression of X_k on Z, X_1, X_2, X_{k-1} is fitted, and the missing values of X_k are imputed.

After 10 iterations, the final imputations of the missing values in X_1, X_2, X_k are used. The entire procedure is repeated independently M times, yielding M imputed datasets.

The use of every variable other than the variable being imputed as a covariate in each regression model; and by sequencing through the regression models, the mi impute chained maintained relationships among the variables are included in the imputation models.

For each regression in the mi impute chained procedure, Stata allows the use of following regression models: `regress`, `pmm`, `truncreg`, `intreg`, `logit`, `ologit`, `mlogit`, `poisson`, and `nbreg`.

All the continuous variables in the KFS are non-negative and for the ones that have missing values, we have the range (contains the lower limit and upper limit) of the missing values, thus using `intreg` insures that the imputed values will be within the range provide by the respondents. Once a range response is used to impute a variable, the imputed value is used as a conditioning variable in all subsequent imputations

In the cases where there is no range provided or convergence issues raised, the

alternative is Predictive Mean Matching (PMM). Since the PMM draws its imputed values from the observed data, the imputed values will never be outside the range of the observed values (honors any bounds that exist in the observed data).

For non-continuous variables an appropriate regression models (pmm, logit, truncreg, intreg) was used based on the nature of the variable and convergence (e.g, logit for indicator variables).

The imputation process is progressive in the sense that we first impute owners' level variables. Given owners level variables (converted to business level characteristics), we impute the rest of variables in series of steps and rounds. The other sequence of imputation was to impute data longitudinally first and then cross-sectional. The number of model specifications in the imputations is very large. In general, we have the same set of explanatory covariates for each imputed variable, which insures consistency across models. Consistency of covariate across models caused problems with variables where only small samples were available. For those variables we select explanatory covariates that fit the models best.

For the fixed core set of variables (asked by all businesses in every survey), we included the lag of the variables. We found that the best predictors of a missing value in one period are the values of that variable in the previous period. In all of model specifications, we control for other elements of the complex sample design of the KFS (strata and weights).

5.1 Wide vs. long format (Original KFS Data)

Both the confidential version of the KFS and the public version data come in a wide format.

Data from a repeated-measures design can be set up in two different data formats: wide and long formats. In the wide format all multi-wave variables from the same business and associated owners form just one record. For example, consider the following data: mprid is the businesses ID and var1_0, var1_1 and var1_2 are the sales for the baseline, first and second follow-up, and var2_0 is the gender of the owner, which was collected in the baseline survey only (time-constant).

mprid	var1_0	var1_1	var1_2	var2_0
1	485	2542	4095	1
2	2724	9292	.	1
3	9924	8049	2966	0

In the long (panel) format data, all variables from each wave and for the same business and associated owners form one record. For example:

mprid	suffix	var1	var2_0
1	_0	485	1
1	_1	2542	1
1	_2	4095	1
2	_0	2724	1
2	_1	9292	1
2	_2	.	1
3	_0	9924	0
3	_1	8049	0
3	_2	2966	0

Two identification variables are needed for the long (panel) format data, in addition to the business ID, we need to have time variable (suffix), but only one variable is needed for the measurements “Var1” and “Var2.”

The long (panel) format is very useful for any longitudinal data analysis of the KFS panel (3,140). Longitudinal businesses that closed in a particular follow-up, sold or merged (records with no information) can be dropped in the long format, but not in the wide format. For example, if the business with ID two was sold in time two, then we can drop that record in time two, and as a result we will be dealing with unbalanced panel data.

mprid	suffix	var1	var2_0
1	_0	485	1
1	_1	2542	1
1	_2	4095	1
2	_0	2724	1
2	_1	9292	1
3	_0	9924	0
3	_1	8049	0
3	_2	2966	0

The advantage of the wide format data is that it is more convenient for the analysis of transitions and sequences, cross-tab (e.g. wave 1 vs. wave 2), lagged regression ($y_t = \alpha + \beta y_{t-1} + \gamma x_{t-1}$), recoding data into soft and hard missing value, logical imputation, defining subpopulation based on time varying variables, survival analysis, cross-sectional analysis and some data manipulation.

5.2 Wide vs. long format (KFS Multiply Imputed Data)

For MI data, the wide vs. long terminology is borrowed from reshape and the structures are similar but are not equivalent. All the KFS Multiply Imputed Data files are formatted using the flong style, which means, in addition to the original KFS data (regardless of the original data format, m=0), we have another five imputed dataset of the KFS (m=1,2,3,4,5).

Example: Wide original KFS - mi flong

m	mprid	var1_0	var1_1	var1_2	var2_0
0	1	485	2542	4095	1
0	2	2724	9292	.	1
0	3	9924	8049	2966	0
1	1	485	2542	4095	1
1	2	2724	9292	Imputed 1	1
1	3	9924	8049	2966	0
2	1	485	2542	4095	1
2	2	2724	9292	Imputed 2	1
2	3	9924	8049	2966	0
3	1	485	2542	4095	1
3	2	2724	9292	Imputed 3	1
3	3	9924	8049	2966	0
4	1	485	2542	4095	1
4	2	2724	9292	Imputed 4	1
4	3	9924	8049	2966	0
5	1	485	2542	4095	1
5	2	2724	9292	Imputed 5	1
5	3	9924	8049	2966	0

Example: long original KFS -mi flong

m	mprid	suffix	var1	var2_0
0	1	_0	485	1
0	1	_1	2542	1
0	1	_2	4095	1
0	2	_0	2724	1
0	2	_1	9292	1
0	2	_2	.	1
0	3	_0	9924	0
0	3	_1	8049	0
0	3	_2	2966	0
1	1	_0	485	1
1	1	_1	2542	1
1	1	_2	4095	1
1	2	_0	2724	1
1	2	_1	9292	1
1	2	_2	Imputed 1	1
1	3	_0	9924	0
1	3	_1	8049	0
1	3	_2	2966	0
2	1	_0	485	1
2	1	_1	2542	1
2	1	_2	4095	1
2	2	_0	2724	1
2	2	_1	9292	1
2	2	_2	Imputed 2	1
2	3	_0	9924	0
2	3	_1	8049	0
2	3	_2	2966	0
3	1	_0	485	1
3	1	_1	2542	1
3	1	_2	4095	1
.
5	3	_0	9924	0
5	3	_1	8049	0
5	3	_2	2966	0

The KFS Multiply Imputed Data files are available in Stata format. The following table shows the names of the files, the number of observations in each file, and the file's format:

File name	Original KFS data	KFS Multiply Imputed Data - format	Number of variables
MI_Flags_wide	Wide (4,928 obs.) : Indicator variables for missing values	NA	7,043
KFS8_LI	Wide: KFS8 after logical imputation.	NA	7,066
KFS8_Cross_Sectional_wide_MI_Long	Wide (4,928 obs.)	Flong (4928*6=29,568 obs.)	5,742
KFS8_Cross_Sectional_Long_MI_Long	Long (4,928*8=39,424 obs.)	Flong (39,424*6=236,544 obs.)	730
KFS8_Longitudinal_wide_MI_Long	Wide (3,140 obs.)	Flong (3,140*6=18,840 obs.)	5,728
KFS8_Longitudinal_Long_MI_Long	Long	Flong (18,286*6=109,716 obs.)	723

While Stata allows other formats (wide, mlong), we do not recommend converting the data to another format. This is due to the fact that when you construct a new variable is could be a super-varying variables in the KFS. You must use the flong format because in the wide and mlong formats, there is simply no place to store super-varying values.

A variable is said to be super varying if its values in the complete observations differ across m, while the existence of super-varying variables is usually an indication of error, it is not the case for the KFS's super-varying variables. The KFS has a complex skip logic that will produce super-varying variables

SPSS Users: while you can import the KFS Multiply Imputed Stata files to SPSS you should be aware that (as of SPSS19) Complex Sampling procedures in SPSS currently do not automatically analyze multiply imputed datasets.

SAS Users: you can import the KFS Multiply Imputed Stata files to SAS. SAS requires only the imputed data sets to be in the file, thus after importing the data to SAS, make sure to drop the original data (m=0). You can do this by using the variable

named master (Keep if master>0). Use MIANALYZE procedures to analyze a multiply imputed dataset.

The following proc import statement will read the xxxx.dta data file and create a temporary data set called mydata.

```
Proc import datafile="Drive:\xxxx.dta" out=mydata dbms = dta replace;
run;
```

Use MIANALYZE procedures to analyze a multiply imputed data set. Also, SAS-callable SUDAAN includes a built-in option for analyzing multiply imputed data.

Super-varying variables are not an issue that you should be worried about in both SAS and SPSS.

5.3 Renamed variables/ Value recoded variables /Newly created variables

To use loops and reshape data efficiently, we need to have the names of the variables to be the same across all the follow-ups.

➤ Renamed variables

To insure consistency of the variables names across all year, the following variables were renamed:

Old	New
fstatus_f2_2	fstatus_2
fstatus_f3_3	fstatus_3
fstatus_f4_4	fstatus_4
fstatus_f5_5	fstatus_5
fstatus_f6_6	fstatus_6
fstatus_f7_7	fstatus_7
b2a_legal_status_0	clz2_legal_status_0
f2_owner_amt_eq_invest_allyrs_15	f2_ownr_amt_eqinvest_allyrs_15_5
f3a_XXXXXXXX	f3_XXXXXXXX
f3b_XXXXXXXX	f3_XXXXXXXX
f3c_XXXXXXXX	f3_XXXXXXXX
f3d_XXXXXXXX	f3_XXXXXXXX
f3e_XXXXXXXX	f3_XXXXXXXX
f3f_XXXXXXXX	f3_XXXXXXXX
f3g_XXXXXXXX	f3_XXXXXXXX
xx_2004_xx	xx_xx
xx_2005_xx	xx_xx
xx_2006_xx	xx_xx
xx_2007_xx	xx_xx
xx_2008_xx	xx_xx
xx_2009_xx	xx_xx
xx_2010_xx	xx_xx

Old	New
xx 2011 xx	xx xx
cswgt final 0	wgt final 0
cswgt final 1	wgt final 1
cswgt final 2	wgt final f2 2
cswgt final 3	wgt final f3 3
cswgt final 4	wgt final f4 4
cswgt final 5	wgt final f5 5
cswgt final 6	wgt final f6 6
cswgt final 7	wgt final f7 7
wgt 1 long	wgt final 1
wgt 2 long	wgt final f12 long 2
wgt 3 long	wgt final f123 long 3
wgt 4 long	wgt final f1234 long 4
wgt 5 long	wgt final f5 long 5
wgt 6 long	wgt final f6 long 6
wgt 7 long	wgt final f7 long 7

➤ Value recoded

For the race categories questions respondents were allowed to report multiracial or mixed-race. Thus, there is a question for each race. Since it is more practical for analysis purposes to have one variable with race coded as categorical variable, we created a new race variable “g6_race_group_xx_y” having the following codes/values:

- American Indian Or Alaska Native 01
- Native Hawaiian Or Other Pacific Islander 02
- Asian 03
- Black Or African American..... 04
- White 05
- Other Races Or Mixed Race..... 06

The g6 questions about race are still in the data, but they have the values 1/0 (yes/no). For owners reported multiracial or mixed-race we recoded them as *other*.

The following table shows the variables that were subject to values recoding, as well as the old and new values:

Variable	New Values	Old Values
g3a oth bus owner	5	6 to ∞
g6 race amind owner	0,1	1
g6 race nathaw owner	0,1	2
g6 race asian owner	0,1	3
g6 race black owner	0,1	4
g6 race white owner	0,1	5
g6 race other owner	0,1	6

Variable	New Values	Old Values
g10 gender owner	0	2
f23 profit or loss	0	2
f7b pers other numused	5	6 to ∞
f9b pers other numused	5	6 to ∞
f11b bus other numused	5	6 to ∞
f7b bus credcard numused	5	6 to ∞
f9b bus credcard numused	5	6 to ∞
f7b pers credcard numused	5	6 to ∞
f7b pers loan fam numused	5	6 to ∞
f9b pers credcard numused	5	6 to ∞
f9b pers loan fam numused	5	6 to ∞
f11b bus credcard numused	5	6 to ∞
f7b pers loan bank numused	5	6 to ∞
f9b pers loan bank numused	5	6 to ∞
f11b bus cred line numused	5	6 to ∞
f11b bus loans emp numused	5	6 to ∞
f11b bus loans fam numused	5	6 to ∞
f7b pers loan other numused	5	6 to ∞
f9b pers loan other numused	5	6 to ∞
f11b bus loans bank numused	5	6 to ∞
f11b bus loans govt numused	5	6 to ∞
f11b bus loans owner numused	5	6 to ∞
f11b bus loans nonbank numused	5	6 to ∞
f11b busloans otherind numused	5	6 to ∞
f11a busloans otherbus numused	5	6 to ∞

➤ Newly created variables

To use loops efficiently, we created the following variables and we set their values to hard missing:

Variable Name	Added to survey	Variable Name	Added to survey
c10_morelocations	0,1	f12f_business_equip_veh	0,1,2,3,4
c11_num_locations	0,1	f12f_business_sec_dep	0,1,2,3,4
c12a_sba	0,1,2,3,5,6,7	f12f_intellectual_prop	0,1,2,3,4
c12b_fed_gov	0,1,2,3,5,6,7	f12f_inventory_acctrec	0,1,2,3,4
c12c_statelocal_gov	0,1,2,3,5,6,7	f12f_other	0,1,2,3,4
c12d_non_profit	0,1,2,3,5,6,7	f12f_other_pers_assets	0,1,2,3,4
c12e_college_univ	0,1,2,3,5,6,7	f12f_pers_real_estate	0,1,2,3,4
c12f_chamber_of_comm	0,1,2,3,5,6,7	f14d_new_loans	0,1,2
c12g_for_profit_org	0,1,2,3,5,6,7	f14e_approved_denied	0,1,2
c12h_other	0,1,2,3,5,6,7	f14f_bus_credit_hist	0,1,2
c9_loc_change_reason	0	f14f_inadeq_doc	0,1,2
d1_a_new_product	0,1,2,3,4	f14f_insuff_coll	0,1,2
d1_b_new_to_market	0,1,2,3,4	f14f_loan_toolarge	0,1,2
d1c_a_regional	0,1,2,3,4	f14f_new_bus	0,1,2
d1c_b_national	0,1,2,3,4	f14f_other	0,1,2

Variable Name	Added to survey	Variable Name	Added to survey
d1c_c_international	0,1,2,3,4	f14f_pers_credit_hist	0,1,2
d1d_new_processes	0,1,2,3,4	f14f_restr_on_lending	0,1,2,3
d2a_compadv_comp_reason	0,1,2	f14g_didnotapply	0,1,2
d2a_compadv_govlab_reason	0,1,2	f14h_loan_guarantees	0,1,2,3
d2a_compadv_patents_reason	0,1,2	f14i_economy_effect	0,1,2,3,5 ,6,7
d2a_compadv_univ_reason	0,1,2	f14j_most_challenging	0,1,2,3
d2b_compadv_comp_strength	0,1,2	f19a_res_dev_amt	0,1,2
d2b_compadv_govlab_strength	0,1,2	f19b_a_design	0,1,2,3
d2b_compadv_patents_strength	0,1,2	f19b_b_investments	0,1,2,3
d2b_compadv_univ_strength	0,1,2	f19b_c_brand_dev	0,1,2,3
d2c_compadv_cost_reason	0,1,2,3,4 ,6,7	f19b_d_org_dev	0,1,2,3
d2c_compadv_design_reason	0,1,2,3,4 ,6,7	f19b_e_worker_training	0,1,2,3
d2c_compadv_expertise_reason	0,1,2,3,4 ,6,7	f19b_f_other	0,1,2,3
d2c_compadv_marketing_reason	0,1,2,3,4 ,6,7	f19c_a_design_amt	0,1,2,3,4
d2c_compadv_price_reason	0,1,2,3,4 ,6,7	f19c_b_investments_amt	0,1,2,3,4
d2c_compadv_reputation_reason	0,1,2,3,4 ,6,7	f19c_c_brand_dev_amt	0,1,2,3,4
d2c_compadv_speed_reason	0,1,2,3,4 ,6,7	f19c_d_org_dev_amt	0,1,2,3,4
d2d_compadv_cost_strength	0,1,2,3,4 ,6,7	f19c_e_worker_training_amt	0,1,2,3,4
d2d_compadv_design_strength	0,1,2,3,4 ,6,7	f19c_f_other_amt	0,1,2,3,4
d2d_compadv_expertise_strength	0,1,2,3,4 ,6,7	f19c_intangassets_amt	0,1,2,3,5 ,6,7
d2d_compadv_marketing_strength	0,1,2,3,4 ,6,7	f32_chap11_bankruptcy	0,1,2,3
d2d_compadv_price_strength	0,1,2,3,4 ,6,7	f33_expected_growth	0,1,2,3,5 ,6,7
d2d_compadv_reput_strength	0,1,2,3,4 ,6,7	f34_future_revenue	0,1,2,3,5 ,6,7
d2d_compadv_speed_strength	0,1,2,3,4 ,6,7	f5a_seek_equity	0,1,2,3,4
d5a_founded_newprod	0,1,2,3,4 ,6,7	f6z_family_owned	0,1,2,3,5 ,6,7
d5b_a_personaluse	0,1,2,3,4 ,6,7	g10b_marital_status	0,1,2,3
d5b_b_previousjob	0,1,2,3,4 ,6,7	g1b2_reasonfor_business	0,1,2,3,4 ,5,6
d5b_c_startingbus	0,1,2,3,4 ,6,7	g10d_personal_outlook	0,1,2,3,5 ,6,7
d8_customer_locations	0,1,2	g10c_net_worth	0,1,2,3
d8a_international_sales	0,1,2	d9a_perc_internet_sales	0,1,2
d8b_perc_international_sales	0,1,2	f12e_collateral	0,1,2,3,4
d9_internet_sales	0,1,2		

For ease of running loops at owner level variables, all survey rounds have owner level variables for 15 owners.

6. Analytic Examples Using Stata® 12.0

6.1 The mi suite of commands: info from the Stata user guide

" The mi suite of commands deals with multiple-imputation data, abbreviated as mi data. In summary,

1. mi data may be stored in one of four formats—flongsep, flong, mlong, and wide—known as styles.
2. mi data contain M imputations numbered $m = 1, 2, \dots, M$, and contain $m = 0$, the original data with missing values.
3. Each variable in mi data is registered as imputed, passive, or regular, or it is unregistered.
 - a. Unregistered variables are mostly treated like regular variables.
 - b. Regular variables usually do not contain missing, or if they do, the missing values are not imputed in $m > 0$.
 - c. Imputed variables contain missing in $m = 0$, and those values are imputed in $m > 0$.
 - d. Passive variables are algebraic combinations of imputed, regular, or other passive variables.
4. If an imputed variable contains a value greater than . in $m = 0$ —it contains .a, .b, . . . , .z—then that value is considered a hard missing and the missing value persists in $m > 0$."

6.1.1 Data Management Commands

➤ Reporting Commands

Command	Function
<code>mi query</code>	Reports whether the data in memory are mi data.
<code>mi describe, nouupdate</code>	Provides a more detailed report on mi data.
<code>mi set</code>	Declare multiple-imputation data
<code>mi xeq</code>	Execute command(s) on individual imputations or on selected ones

```
use KFS8_Cross_Sectional_wide_MI_Long,clear
(KFS8 Cross Sectional in wide format & Multiply Imputed Data in long
format)
```

```
mi query
```

```
data mi set flong, M = 5
```

```
mi describe,noupdate
```

```
Style: flong

Obs.: complete      0
      incomplete    4,928      (M = 5 imputations)
-----
      total         4,928

Vars.: imputed: 0
      passive: 0
      regular: 1; mprid
      system: 3; _mi_m _mi_id _mi_miss
      (there are 5738 unregistered variables)
```

```
mi misstable summarize c5_*
```

Variable	Obs=.	Obs>.	Obs<.	Obs<.		
				Unique values	Min	Max
c5_num_emp~0	105		4,823	49	0	165
c5_num_emp~1	46	930	3,952	63	0	1100
c5_num_emp~2	37	1,538	3,353	62	0	160
c5_num_emp~3	25	2,013	2,890	60	0	350
c5_num_emp~4	4	2,322	2,602	63	0	320
c5_num_emp~5	10	2,520	2,398	63	0	265
c5_num_emp~6	5	2,802	2,121	58	0	400
c5_num_emp~7	7	2,921	2,000	71	0	900

All KFS multiply imputed data files already declared to be multiple-imputation data, thus do not use `mi set`.

➤ Setting mi Data

Commands like `svyset`, `stset`, and `xtset` also have mi versions: use `mi svyset` to declare survey data, use `mi stset` to declare survival data, and use `mi xtset` to declare panel data.

```
use KFS8_Cross_Sectional_wide_MI_Long,clear
(KFS8 Cross Sectional in wide format & Multiply Imputed Data in long format)

mi svyset [pweight=cswgt_final_0], strata(sampleinfo_samplestrata_0)

    pweight: cswgt_final_0
        VCE: linearized
Single unit: missing
  Strata 1: sampleinfo_samplestrata_0
    SU 1: <observations>
    FPC 1: <zero>

* sts is not supported by svy nor mi

mi stset Duration [pweight=cswgt_final_0] , failure(event==1)

    pweight: cswgt_final_0
        VCE: linearized
Single unit: missing
  Strata 1: sampleinfo_samplestrata_0
    SU 1: <observations>
    FPC 1: <zero>

. mi stset Duration [pweight=cswgt_final_0] , failure(event==1)

    failure event:  event == 1
obs. time interval:  (0, Duration]
  exit on or before:  failure
    weight:  [pweight=cswgt_final_0]

-----
    4928  total obs.
         0  exclusions
-----

    4928  obs. remaining, representing
    2190  failures in single record/single failure data
    27568  total analysis time at risk, at risk from t =          0
                                     earliest observed entry t =          0
                                     last observed exit t =          8

use KFS8_Longitudinal_Long_MI_Long,clear
(KFS8 Longitudinal in long format & Multiply Imputed Data in long format)

mi xtset mprid year
    panel variable:  mprid (unbalanced)
    time variable:  year, 2004 to 2011
                  delta:  1 unit

mi xeq 0:  xtdescribe

mprid:  10000016, 10000090, ..., 10324611          n =          3140
year:   2004, 2005, ..., 2011                    T =           8
Delta(year) = 1 unit
Span(year) = 8 periods
```

```

(mprid*year uniquely identifies each observation)
Distribution of T_i:  min      5%      25%      50%      75%      95%      max
                   1        1        3        8        8        8        8

   Freq.  Percent   Cum. | Pattern
-----+-----
   1630    51.91   51.91 | 11111111
    303     9.65   61.56 | 1.....
    283     9.01   70.57 | 11.....
    238     7.58   78.15 | 1111....
    224     7.13   85.29 | 111.....
    164     5.22   90.51 | 11111...
    153     4.87   95.38 | 111111..
    145     4.62  100.00 | 1111111.
-----+-----
    3140   100.00          | xxxxxxxx

mi svyset [pweight=wgt_7_long], strata(sampleinfo_samplestrata)

    pweight: wgt_7_long
           VCE: linearized
Single unit: missing
  Strata 1: sampleinfo_samplestrata
    SU 1: <observations>
    FPC 1: <zero>

```

6.1.2 Creating or Changing Variables

In Stata , the definitions of MI variables are:

1. A regular variable is a variable that is neither imputed nor passive and that has the same values, whether missing or not, in all m. (e.g., c4_numowners_confirm)
2. An imputed variable is a variable that has missing values and for which you have imputations. An imputed variable will have missing values in m = 0 and varying values for observations in m > 0.
3. A passive variable is a varying variable that is a function of imputed variables or of other passive variables. A passive variable will have missing values in m = 0 and varying values for observations in m > 0.

Two other definitions that they use in the manual, the definitions for varying and super varying.

4. Varying: a variable is said to be varying if its values in the incomplete observations (missing) differ across imputations. Imputed and passive variables are varying. Regular variables are nonvarying. Unregistered variables can be either.

5. Super varying: a variable is said to be super varying if its values in the complete observations (no missing in m=0) differ across imputations.

The distinction between varying variables and super-varying variables allows -mi- to detect inconsistencies among complete observations across imputations and fix such inconsistencies. Variables that are functions of the values of other imputed variables are likely to be super-varying (e.g., skip logic)

6.1.2.1 Creating or Changing Variables - Regular Variables

New or changed variable that is functions of existing regular variables are also regular variable. Use `mi xeq` to create new regular variable or change the value of existing regular variable.

Example of regular variables in KFS

mprid
b1_bus_start
c1z2_legal_status
c2_owners
c3a_owner_operators
c4_numowners_confirm
d1a_provide_service
d1b_provide_product
c8_primary_loc
hightech
techempl
techgenr
naics_code
sampleinfo_samplestrata
website
email


```

use KFS8_Cross_Sectional_wide_MI_Long,clear
(KFS8 Cross Sectional in wide format & Multiply Imputed Data in long format)

mi xeq: recode c8_primary_loc_0 (2/5=0)
m=0 data:
-> recode c8_primary_loc_0 (2/5=0)
(c8_primary_loc_0: 2437 changes made)

m=1 data:
-> recode c8_primary_loc_0 (2/5=0)
(c8_primary_loc_0: 2437 changes made)

m=2 data:
-> recode c8_primary_loc_0 (2/5=0)
(c8_primary_loc_0: 2437 changes made)

m=3 data:
-> recode c8_primary_loc_0 (2/5=0)
(c8_primary_loc_0: 2437 changes made)

m=4 data:
-> recode c8_primary_loc_0 (2/5=0)
(c8_primary_loc_0: 2437 changes made)

m=5 data:
-> recode c8_primary_loc_0 (2/5=0)
(c8_primary_loc_0: 2437 changes made)

mi xeq: gen provide_service_product_1=(dla_provide_service_1== ///
dlb_provide_product_1 ==1) if dla_provide_service_1<. & ///
dla_provide_service_1<.

m=0 data:
-> gen
provide_service_product_1=(dla_provide_service_1==dlb_provide_product_1==1) if
dla_provide_service_1<. & dla_provide_service_1<.
(930 missing values generated)

m=1 data:
-> gen
provide_service_product_1=(dla_provide_service_1==dlb_provide_product_1==1) if
dla_provide_service_1<. & dla_provide_service_1<.
(930 missing values generated)

m=2 data:
-> gen
provide_service_product_1=(dla_provide_service_1==dlb_provide_product_1==1) if
dla_provide_service_1<. & dla_provide_service_1<.
(930 missing values generated)

m=3 data:
-> gen
provide_service_product_1=(dla_provide_service_1==dlb_provide_product_1==1) if
dla_provide_service_1<. & dla_provide_service_1<.
(930 missing values generated)

m=4 data:
-> gen
provide_service_product_1=(dla_provide_service_1==dlb_provide_product_1==1) if
dla_provide_service_1<. & dla_provide_service_1<.
(930 missing values generated)

```

```

m=5 data:
-> gen
provide_service_product_1=(d1a_provide_service_1==d1b_provide_product_1==1) if
d1a_provide_service_1<. & d1a_provide_service_1<.
(930 missing values generated)

mi xeq: replace provide_service_product_1=.a if classf_1<6

m=0 data:
-> replace provide_service_product_1=.a if classf_1<6
(930 real changes made, 930 to missing)

m=1 data:
-> replace provide_service_product_1=.a if classf_1<6
(930 real changes made, 930 to missing)

m=2 data:
-> replace provide_service_product_1=.a if classf_1<6
(930 real changes made, 930 to missing)

m=3 data:
-> replace provide_service_product_1=.a if classf_1<6
(930 real changes made, 930 to missing)

m=4 data:
-> replace provide_service_product_1=.a if classf_1<6
(930 real changes made, 930 to missing)

m=5 data:
-> replace provide_service_product_1=.a if classf_1<6
(930 real changes made, 930 to missing)

```

6.1.2.2 Creating or Changing Variables - Passive variables

A passive variable is a function of imputed variables. Use `mi passive` followed by `gen` or `replace` commands to generate/replace and register passive variables. You can use `mi passive` with any function that produces values that solely depend on values within the observation. In general, you cannot use `mi passive` with functions that produce values that depend on groups of observations.

You can use `mi passive` only with the variables that already registered. You should be careful not to mistakenly use `mi passive` to create super-varying variables.

We already register the varying variables in the KFS MI files. All variables were checked for consistency across imputation and were registered correctly. You can use the command "`mi varying`" to see the registered / unregistered variables.

```

use KFS8_Cross_Sectional_wide_MI_Long,clear
(KFS8 Cross Sectional in wide format & Multiply Imputed Data in long format)

```

```

mi passive : gen          tot_assets_0 = f29_assetval_acctrec_0 +
f29_assetval_cash_0 + f29_assetval_equip_0 + f29_assetval_inv_0 +
f29_assetval_landbuild_0 + f29_assetval_othbusprop_0 +
f29_assetval_other_0 + f29_assetval_veh_0
m=0:(1046 missing values generated)
m=1:
m=2:
m=3:
m=4:
m=5:

mi passive : egen          tot_assets_0= rowtotal(f29_assetval_acctrec_0
f29_assetval_cash_0          f29_assetval_equip_0          f29_assetval_inv_0
f29_assetval_landbuild_0    f29_assetval_othbusprop_0    f29_assetval_other_0
f29_assetval_veh_0),missing
m=0: (21 missing values generated)
m=1:
m=2:
m=3:
m=4:
m=5:

mi passive : egen pr_race_w_0 =rowmean( g6_race_white_owner_*_0)
m=0:(11 missing values generated)
m=1:
m=2:
m=3:
m=4:
m=5:

```

6.1.2.3 Creating or Changing Variables - Super-varying Variables

A super-varying variable is generated when the variable value is a function of the values of other imputed variables. Thus, its values in the complete observations (m=0) differ across m.

A super-varying variable could be a result of a skip logic where the sample varies across imputations, incorrect flow through prescribed skip patterns, or/and inconsistency in values after editing the raw data.

In the long format, a super-varying variable is generated when the variable value is a function of the values of imputed variables for other observations.

Super-varying variables must not be registered

Use `mi xeq` followed by `gen`, `egen` or `replace` commands to generate/replace super-varying variables.

```

use KFS8_Cross_Sectional_wide_MI_Long,clear
(KFS8 Cross Sectional in wide format & Multiply Imputed Data in long format)

mi xeq :egen tot_ex_equity_0= rowtotal(f4_eq_amt_spouse_all yrs_0
f4_eq_amt_parents_all yrs_0 f4_eq_amt_angels_all yrs_0
f4_eq_amt_companies_all yrs_0 f4_eq_amt_govt_all yrs_0

```

```
f4_eq_amt_vent_cap_allyrs_0 f4_eq_amt_other_allyrs_0),missing
```

```
m=0 data:
```

```
-> egen tot_ex_equity_0= rowtotal(f4_eq_amt_spouse_allyrs_0  
f4_eq_amt_parents_allyrs_0 f4_eq_amt_angels_allyrs_0 f4_eq_amt_companies_allyrs_0  
f4_eq_amt_govt_allyrs_0 f4_eq_amt_vent_cap_allyrs_0  
f4_eq_amt_other_allyrs_0),missing  
(2588 missing values generated)
```

```
m=1 data:
```

```
-> egen tot_ex_equity_0= rowtotal(f4_eq_amt_spouse_allyrs_0  
f4_eq_amt_parents_allyrs_0 f4_eq_amt_angels_allyrs_0 f4_eq_amt_companies_allyrs_0  
f4_eq_amt_govt_allyrs_0 f4_eq_amt_vent_cap_allyrs_0  
f4_eq_amt_other_allyrs_0),missing  
(2576 missing values generated)
```

```
m=2 data:
```

```
-> egen tot_ex_equity_0= rowtotal(f4_eq_amt_spouse_allyrs_0  
f4_eq_amt_parents_allyrs_0 f4_eq_amt_angels_allyrs_0 f4_eq_amt_companies_allyrs_0  
f4_eq_amt_govt_allyrs_0 f4_eq_amt_vent_cap_allyrs_0  
f4_eq_amt_other_allyrs_0),missing  
(2576 missing values generated)
```

```
m=3 data:
```

```
-> egen tot_ex_equity_0= rowtotal(f4_eq_amt_spouse_allyrs_0  
f4_eq_amt_parents_allyrs_0 f4_eq_amt_angels_allyrs_0 f4_eq_amt_companies_allyrs_0  
f4_eq_amt_govt_allyrs_0 f4_eq_amt_vent_cap_allyrs_0  
f4_eq_amt_other_allyrs_0),missing  
(2576 missing values generated)
```

```
m=4 data:
```

```
-> egen tot_ex_equity_0= rowtotal(f4_eq_amt_spouse_allyrs_0  
f4_eq_amt_parents_allyrs_0 f4_eq_amt_angels_allyrs_0 f4_eq_amt_companies_allyrs_0  
f4_eq_amt_govt_allyrs_0 f4_eq_amt_vent_cap_allyrs_0  
f4_eq_amt_other_allyrs_0),missing  
(2576 missing values generated)
```

```
m=5 data:
```

```
-> egen tot_ex_equity_0= rowtotal(f4_eq_amt_spouse_allyrs_0  
f4_eq_amt_parents_allyrs_0 f4_eq_amt_angels_allyrs_0 f4_eq_amt_companies_allyrs_0  
f4_eq_amt_govt_allyrs_0 f4_eq_amt_vent_cap_allyrs_0  
f4_eq_amt_other_allyrs_0),missing  
(2576 missing values generated)
```

```
mi xeq : mean tot_ex_equity_0
```

```
m=0 data:
```

```
-> mean tot_ex_equity_0
```

```
Mean estimation                Number of obs    =    2340
```

```
-----  
          |          Mean   Std. Err.   [95% Conf. Interval]  
-----+-----  
tot_ex_equity_0 |      126749    35987.7    56177.88    197320.1  
-----
```

```
m=1 data:
```

```
-> mean tot_ex_equity_0
```

```
Mean estimation                Number of obs    =    2352
```

```
-----+-----
              |          Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    131588.3   35971.22    61049.66    202126.9
-----+-----
```

```
m=2 data:
-> mean tot_ex_equity_0
```

```
Mean estimation                Number of obs   =    2352
```

```
-----+-----
              |          Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    131219.8   36010.29    60604.58    201835
-----+-----
```

```
m=3 data:
-> mean tot_ex_equity_0
```

```
Mean estimation                Number of obs   =    2352
```

```
-----+-----
              |          Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    131090.2   35951.89    60589.51    201590.9
-----+-----
```

```
m=4 data:
-> mean tot_ex_equity_0
```

```
Mean estimation                Number of obs   =    2352
```

```
-----+-----
              |          Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    131320.4   35967.15    60789.76    201851
-----+-----
```

```
m=5 data:
-> mean tot_ex_equity_0
```

```
Mean estimation                Number of obs   =    2352
```

```
-----+-----
              |          Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    132369    35973.14    61826.6    202911.3
-----+-----
```

What if we use mi passive?

```
use KFS8_Cross_Sectional_wide_MI_Long,clear
(KFS8 Cross Sectional in wide format & Multiply Imputed Data in long format)

mi passive : egen tot_ex_equity_0= rowtotal(f4_eq_amt_spouse_allyrs_0
f4_eq_amt_parents_allyrs_0 f4_eq_amt_angels_allyrs_0
f4_eq_amt_companies_allyrs_0 f4_eq_amt_govt_allyrs_0
f4_eq_amt_vent_cap_allyrs_0 f4_eq_amt_other_allyrs_0),missing
m=0: (2588 missing values generated)
m=1: (2576 missing values generated)
```

```

m=2:(2576 missing values generated)
m=3:(2576 missing values generated)
m=4:(2576 missing values generated)
m=5:(2576 missing values generated)
(451 values of passive variable tot_ex_equity_0 in m>0 updated to match values in
m=0)

```

```
mi xeq : mean tot_ex_equity_0
```

```
m=0 data:
-> mean tot_ex_equity_0
```

```

Mean estimation           Number of obs   =    2340

-----+-----
           |           Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    126749    35987.7    56177.88    197320.1
-----+-----

```

```
m=1 data:
-> mean tot_ex_equity_0
```

```

Mean estimation           Number of obs   =    2340

-----+-----
           |           Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    126749    35987.7    56177.88    197320.1
-----+-----

```

```
m=2 data:
-> mean tot_ex_equity_0
```

```

Mean estimation           Number of obs   =    2340

-----+-----
           |           Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    126749    35987.7    56177.88    197320.1
-----+-----

```

```
m=3 data:
-> mean tot_ex_equity_0
```

```

Mean estimation           Number of obs   =    2340

-----+-----
           |           Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |    126749    35987.7    56177.88    197320.1
-----+-----

```

```
m=4 data:
-> mean tot_ex_equity_0
```

```

Mean estimation           Number of obs   =    2340

-----+-----
           |           Mean   Std. Err.   [95% Conf. Interval]
-----+-----

```

```

-----+-----
tot_ex_equity_0 |      126749   35987.7   56177.88   197320.1
-----+-----

m=5 data:
-> mean tot_ex_equity_0

Mean estimation          Number of obs   =      2340

-----+-----
              |      Mean   Std. Err.   [95% Conf. Interval]
-----+-----
tot_ex_equity_0 |      126749   35987.7   56177.88   197320.1
-----+-----

```

Since that the `f4_eq_amt_xxxx_allyrs` variables are not registered, mistakenly use `mi passive` to create super-varying variables will trigger an automatic update by Stata. The results of such update is that all the data for this variable in the imputed data (`m=1, 2, 3, 4, 5`) will be replaced by the data in the original data (`m=0`).

Leaving newly created variables unregistered makes `mi update` leave them alone. So, it is always safer to use `mi xeq` when you create any new variable.

6.1.3 Estimating

Multiple-imputation data analysis in Stata is similar to standard data analysis. All what we have to do is to prefix the estimation commands with `mi estimate`:

The following estimation commands support the `mi estimate` prefix.

Linear regression models

`regress` Linear regression
`cnsreg` Constrained linear regression
`mvreg` Multivariate regression

Binary-response regression models

`logistic` Logistic regression, reporting odds ratios
`logit` Logistic regression, reporting coefficients
`probit` Probit regression
`cloglog` Complementary log-log regression
`binreg` GLM for the binomial family

Count-response regression models

`poisson` Poisson regression
`nbreg` Negative binomial regression
`gnbreg` Generalized negative binomial regression

Ordinal-response regression models

`ologit` Ordered logistic regression

oprobit Ordered probit regression

Categorical-response regression models

mlogit Multinomial (polytomous) logistic regression

mprobit Multinomial probit regression

clogit Conditional (fixed-effects) logistic regression

Quantile regression models

qreg Quantile regression

iqreg Interquantile range regression

sqreg Simultaneous-quantile regression

bsqreg Bootstrapped quantile regression

Survival regression models

stcox Cox proportional hazards model

streg Parametric survival models

stcrreg Competing-risks regression

Other regression models

glm Generalized linear models

areg Linear regression with a large dummy-variable set

rreg Robust regression

truncreg Truncated regression

Descriptive statistics

mean Estimate means

proportion Estimate proportions

ratio Estimate ratios

total Estimate totals

Panel-data models

xtreg Fixed-, between- and random-effects, and population-averaged linear models

xtmixed Multilevel mixed-effects linear regression

xtrc Random-coefficients regression

xtlogit Fixed-effects, random-effects, and population-averaged logit models

xtprobit Random-effects and population-averaged probit models

xtcloglog Random-effects and population-averaged cloglog models

xtpoisson Fixed-effects, random-effects, and population-averaged Poisson models

xtnbreg Fixed-effects, random-effects, and PA negative binomial models

xtmelogit Multilevel mixed-effects logistic regression

xtmepoisson Multilevel mixed-effects Poisson regression

xtgee Fit population-averaged panel-data models by using GEE

Survey regression models

svy Estimation commands for survey data

6.1.4 Examples – KFS wide MI style long

```
use KFS8_Cross_Sectional_wide_MI_Long, clear
(KFS8 Cross Sectional in wide format & Multiply Imputed Data in long format)

*Calculating Company-Level Characteristics - equally weighted - 2004 only
```



```

forvalues i = 0/0 {
mi xeq :egen s_owner_amt_eq_invest_`i'=rowtotal
(f2_owner_amt_eq_invest_*_`i')
mi xeq :egen s_hours_owner_`i'          =   rowtotal
(g1b1_hours_owner_*_`i')
mi xeq :egen m_work_exp_owner_`i'      =   rowmean
(g2_work_exp_owner_*_`i')
mi xeq :egen m_age_owner_`i' =          rowmean (   g4_age_owner_*_`i')
mi xeq :egen pr_emp_owner_`i' =rowmean   (   gla_emp_owner_*_`i')
mi xeq :egen pr_hisp_origin_owner_`i' = rowmean   (
g5_hisp_origin_owner_*_`i')
mi xeq :egen pr_native_born_owner_`i' = rowmean   (
g7_native_born_owner_*_`i')
mi xeq :egen pr_gender_owner_`i'      =   rowmean   (
g10_gender_owner_*_`i')
mi xeq :egen      pr_race_w_`i'        =   rowmean   (
g6_race_white_owner_*_`i')
mi xeq :egen      pr_race_a_`i'        =   rowmean   (
g6_race_asian_owner_*_`i')
mi xeq :egen      pr_race_b_`i'        =   rowmean   (
g6_race_black_owner_*_`i')
mi xeq :egen      pr_race_o_`i'        =   rowmean   (
g6_race_other_owner_*_`i')
mi xeq :egen      pr_race_na_`i'       =   rowmean   (
g6_race_nathaw_owner_*_`i')
mi xeq :egen      pr_race_am_`i'       =   rowmean   (
g6_race_amind_owner_*_`i')
mi xeq :gen      homebased_`i'=(c8_primary_loc_`i'==1)
mi xeq :egen      tot_assets_`i'=      rowtotal(f29_assetval_acctrec_`i'
f29_assetval_cash_`i'      f29_assetval_equip_`i'      f29_assetval_inv_`i'
f29_assetval_landbuild_`i'      f29_assetval_othbusprop_`i'
f29_assetval_other_`i' f29_assetval_veh_`i')
}

forvalues i = 0/0 {
mi xeq :replace s_owner_amt_eq_invest_`i' =.a if classf_`i'<6
mi xeq :replace s_hours_owner_`i'        =.a if classf_`i'<6
mi xeq :replace m_work_exp_owner_`i'     =.a if classf_`i'<6
mi xeq :replace m_age_owner_`i'         =.a if classf_`i'<6
mi xeq :replace pr_emp_owner_`i'        =.a if classf_`i'<6
mi xeq :replace pr_hisp_origin_owner_`i' =.a if classf_`i'<6
mi xeq :replace pr_native_born_owner_`i' =.a if classf_`i'<6
mi xeq :replace pr_gender_owner_`i'     =.a if classf_`i'<6
mi xeq :replace pr_race_w_`i'          =.a if classf_`i'<6
mi xeq :replace pr_race_a_`i'          =.a if classf_`i'<6
mi xeq :replace pr_race_b_`i'          =.a if classf_`i'<6
mi xeq :replace pr_race_o_`i'          =.a if classf_`i'<6
mi xeq :replace pr_race_na_`i'         =.a if classf_`i'<6
mi xeq :replace pr_race_am_`i'         =.a if classf_`i'<6
mi xeq :replace      homebased_`i'      =.a if classf_`i'<6
mi xeq :replace      tot_assets_`i'     =.a if classf_`i'<6
}

mi svyset [pweight=cswgt_final_0], strata(sampleinfo_samplestrata_0)

```

➤ **Descriptive statistics**

mi estimate: svy: mean pr*_0

```

Multiple-imputation estimates      Imputations      =          5
Survey: Mean estimation           Number of obs    =         4928

Number of strata =                6      Population size = 73278.441
Number of PSUs   =               4928

Average RVI      =          0.0042
Largest FMI     =          0.0159
Complete DF     =          4922
DF adjustment:  Small sample      DF:      min    =         3720.43
                                           avg    =         4717.88
                                           max    =         4919.96

Within VCE type:  Linearized
  
```

	Mean	Std. Err.	[95% Conf. Interval]	
pr_emp_owner_0	.4697238	.0079859	.4540679	.4853797
pr_hisp_origin_owner_0	.0656113	.0040787	.0576153	.0736074
pr_native_born_owner_0	.8880152	.0050114	.8781907	.8978397
pr_gender_owner_0	.6775468	.0053296	.6670985	.6879951
pr_race_w_0	.8089889	.0064614	.7963216	.8216562
pr_race_a_0	.0379152	.0030877	.0318618	.0439685
pr_race_b_0	.0854109	.0046647	.0762661	.0945558
pr_race_o_0	.0511647	.0036271	.0440533	.0582761
pr_race_na_0	.0058139	.00133	.0032065	.0084213
pr_race_am_0	.0107064	.0016509	.0074697	.0139431

*Based on available-cases - not complete cases

mi xeq 0: svy: mean pr*_0

```

m=0 data:
-> svy: mean pr*_0
(running mean on estimation sample)
  
```

Survey: Mean estimation

```

Number of strata =                6      Number of obs    =         4887
Number of PSUs   =               4887      Population size  =         72617
                                           Design df       =         4881
  
```

	Mean	Linearized Std. Err.	[95% Conf. Interval]	
pr_emp_owner_0	.4691385	.0080128	.4534298	.4848471
pr_hisp_origin_owner_0	.0654262	.0040914	.0574052	.0734472
pr_native_born_owner_0	.8886723	.0050182	.8788343	.8985103
pr_gender_owner_0	.6774446	.0053524	.6669515	.6879377
pr_race_w_0	.809692	.0064732	.7970017	.8223824
pr_race_a_0	.0373706	.0030706	.0313508	.0433904
pr_race_b_0	.0858202	.0046952	.0766155	.0950249
pr_race_o_0	.0508361	.0036048	.0437691	.0579031
pr_race_na_0	.0058605	.0013419	.0032297	.0084913
pr_race_am_0	.0104205	.001627	.0072309	.0136102

```

mi estimate: svy:          proportion g6b_race_group_01_0

Multiple-imputation estimates      Imputations      =          5
Survey: Proportion estimation      Number of obs     =         4928

Number of strata =          6      Population size = 73278.441
Number of PSUs  =         4928

Average RVI      =          0.0087
Largest FMI     =          0.0200
Complete DF     =          4922
DF adjustment:  Small sample      DF:      min     =        3275.22
                                           avg     =        4393.06
                                           max     =        4920.00
Within VCE type:  Linearized

  _prop_1: g6b_race_group_01_0 = American Indian Or Alaska Native
  _prop_2: g6b_race_group_01_0 = Native Hawaiian Or Other Pacific
  _prop_4: g6b_race_group_01_0 = Black Or African American
  _prop_6: g6b_race_group_01_0 = Other Races Or Mixed Race

```

	Proportion	Std. Err.	[95% Conf. Interval]	
_prop_1	.0118408	.0018489	.0082159	.0154658
_prop_2	.0056011	.0013188	.0030156	.0081865
Asian	.0362738	.0031042	.0301881	.0423596
_prop_4	.0857726	.0047379	.0764842	.095061
White	.8100227	.0066022	.7970793	.8229661
_prop_6	.050489	.0037277	.0431801	.057798

```

mi estimate: svy:          total      c5_num_employees_0

Multiple-imputation estimates      Imputations      =          5
Survey: Total estimation          Number of obs     =         4928

Number of strata =          6      Population size = 73278.441
Number of PSUs  =         4928

Average RVI      =          0.0064
Largest FMI     =          0.0064
Complete DF     =          4922
DF adjustment:  Small sample      DF:      min     =        4658.43
                                           avg     =        4658.43
                                           max     =        4658.43
Within VCE type:  Linearized

```

	Total	Std. Err.	[95% Conf. Interval]	
c5_num_employees_0	136511.5	6687.389	123401.1	149622

mi estimate: svy: ratio ft_0: c6_num_ft_employees_0/c5_num_employees_0

```

Multiple-imputation estimates      Imputations      =          5
Survey: Ratio estimation           Number of obs    =         4928

Number of strata =                 6      Population size = 73278.441
Number of PSUs  =                 4928

Average RVI      =         0.0093
Largest FMI     =         0.0093
Complete DF     =          4922
DF adjustment:  Small sample      DF:      min    =         4413.69
                                           avg      =         4413.69
Within VCE type:  Linearized      max      =         4413.69
  
```

ft_0: c6_num_ft_employees_0/c5_num_employees_0

	Ratio	Std. Err.	[95% Conf. Interval]	
ft_0	.6506912	.0182751	.6148629	.6865195

mi estimate: svy: ratio ft_0: c6_num_ft_employees_0/c5_num_employees_0, over(homebased_0)

```

Multiple-imputation estimates      Imputations      =          5
Survey: Ratio estimation           Number of obs    =         4928

Number of strata =                 6      Population size = 73278.441
Number of PSUs  =                 4928

Average RVI      =         0.0089
Largest FMI     =         0.0093
Complete DF     =          4922
DF adjustment:  Small sample      DF:      min    =         4410.21
                                           avg      =         4455.66
Within VCE type:  Linearized      max      =         4501.12
  
```

ft_0: c6_num_ft_employees_0/c5_num_employees_0

0: homebased_0 = 0
1: homebased_0 = 1

Over	Ratio	Std. Err.	[95% Conf. Interval]	
0	.6587501	.0214913	.6166163	.7008838
1	.6117805	.0242893	.5641615	.6593994

➤ Regression

```
mi estimate, post: svy: reg f24_profitloss_amt_0 pr_gender_owner_0
pr_race_w_0 pr_hisp_origin_owner_0 m_age_owner_0 pr_native_born_owner_0
i.homebased_0
```

```
Multiple-imputation estimates      Imputations      =      5
Survey: Linear regression          Number of obs    =     4928

Number of strata =      6          Population size   = 73278.441
Number of PSUs  =     4928

Average RVI      =     0.1515
Largest FMI     =     0.3027
Complete DF     =     4922
DF:             min      =     51.57
               avg      =    1155.88
               max      =     4640.70

Model F test:      Equal FMI      F( 6, 704.3)    =     4.39
Within VCE type:  Linearized      Prob > F        =     0.0002
```

f24_profitloss_amt_0	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pr_gender_owner_0	-1215.076	4182.292	-0.29	0.772	-9430.876	7000.724
pr_race_w_0	-3162.242	4065.806	-0.78	0.437	-11157.76	4833.277
pr_hisp_origin_owner_0	-1511.337	5834.695	-0.26	0.797	-13221.82	10199.14
m_age_owner_0	-389.5985	284.4032	-1.37	0.171	-947.5724	168.3754
pr_native_born_owner_0	6998.205	5471.778	1.28	0.201	-3746.241	17742.65
l.homebased_0	13849.18	4833.538	2.87	0.004	4373.153	23325.21
_cons	4017.858	12905.33	0.31	0.756	-21324.63	29360.35

```
estimates store mi
```

```
mi xeq 0: svy: reg f24_profitloss_amt_0 pr_gender_owner_0
pr_race_w_0 pr_hisp_origin_owner_0 m_age_owner_0 pr_native_born_owner_0
i.homebased_0
```

```
m=0 data:
```

```
-> svy: reg f24_profitloss_amt_0 pr_gender_owner_0 pr_race_w_0 pr_hisp_origin_owner_0
m_age_owner_0 pr_native_born_owner_0 i.homebased_0
(running regress on estimation sample)
```

```
Survey: Linear regression
```

```
Number of strata =      6          Number of obs    =     4130
Number of PSUs  =     4130        Population size   = 61202.686
Design df       =     4124
F( 6, 4119)    =     5.47
Prob > F       =     0.0000
R-squared      =     0.0015
```

f24_profitloss_amt_0	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pr_gender_owner_0	-1629.636	4457.54	-0.37	0.715	-10368.82	7109.547
pr_race_w_0	-2732.914	4280.3	-0.64	0.523	-11124.61	5658.783
pr_hisp_origin_owner_0	-2681.984	5151.077	-0.52	0.603	-12780.87	7416.906
m_age_owner_0	-439.5909	324.9976	-1.35	0.176	-1076.761	197.5796
pr_native_born_owner_0	5401.048	5771.056	0.94	0.349	-5913.335	16715.43
l.homebased_0	14759.29	5691.326	2.59	0.010	3601.217	25917.35
cons	6741.159	14366.55	0.47	0.639	-21425.03	34907.35

```
estimates store cc
```

estimates table cc mi, b se p

Variable	cc	mi
pr_gender_~0	-1629.6358	-1215.0758
	4457.5399	4182.2918
	0.7147	0.7714
pr_race_w_0	-2732.9137	-3162.2421
	4280.3	4065.8063
	0.5232	0.4367
pr_hisp_or~0	-2681.9838	-1511.3371
	5151.077	5834.6951
	0.6026	0.7956
m_age_owne~0	-439.59093	-389.59851
	324.99756	284.40319
	0.1763	0.1708
pr_native_~0	5401.0483	6998.2053
	5771.0565	5471.7782
	0.3494	0.2010
homebased_0		
1	14759.286	13849.184
	5691.326	4833.5375
	0.0095	0.0042
_cons	6741.1588	4017.858
	14366.55	12905.333
	0.6389	0.7556

legend: b/se/p

mi estimate: svy: logit f2_owner_eq_invest_01_0
 i.g10_gender_owner_01_0 glb1_hours_owner_01_0 i.g5_hisp_origin_owner_01_0
 g4_age_owner_01_0 i.g6_race_white_owner_01_0 tot_assets_0 i.homebased_0

Multiple-imputation estimates	Imputations	=	5
Survey: Logistic regression	Number of obs	=	4928
Number of strata =	6	Population size	= 73278.441
Number of PSUs =	4928	Average RVI	= 0.0049
		Largest FMI	= 0.0149
		Complete DF	= 4922
DF adjustment: Small sample	DF: min	=	3836.47
	avg	=	4574.53
	max	=	4919.50
Model F test: Equal FMI	F(7, 4884.5)	=	3.29
Within VCE type: Linearized	Prob > F	=	0.0017

f2 owner eq invest 01 0	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
1.g10_gender_owner_01_0	-.0510739	.0921519	-0.55	0.579	-.2317328 .129585
glb1_hours_owner_01_0	.0078883	.0018613	4.24	0.000	.0042394 .0115372
1.g5_hisp_origin_own~01_0	-.2070301	.1671076	-1.24	0.215	-.5346356 .1205753
g4_age_owner_01_0	.0053884	.0039348	1.37	0.171	-.0023261 .013103
1.g6_race_white_owne~01_0	.0209044	.1076682	0.19	0.846	-.1901759 .2319847
tot_assets_0	1.66e-08	1.43e-08	1.17	0.243	-1.13e-08 4.46e-08
1.homebased_0	.032439	.0867136	0.37	0.708	-.1375593 .2024372
_cons	.8194928	.225925	3.63	0.000	.3765719 1.262414

```
mi xeq 0: svy:  logit f2_owner_eq_invest_01_0    i.g10_gender_owner_01_0
glbl_hours_owner_01_0    i.g5_hisp_origin_owner_01_0    g4_age_owner_01_0
i.g6_race_white_owner_01_0    tot_assets_0 i.homebased_0
```

```
m=0 data:
-> svy:  logit f2_owner_eq_invest_01_0    i.g10_gender_owner_01_0    glbl_hours_owner_01_0
i.g5_hisp_origin_owner_01_0    g4_age_owner_01_0    i.g6_race_white_owner_01_0    tot_assets_0
i.homebased_0
(running logit on estimation sample)
```

Survey: Logistic regression

```
Number of strata =      6
Number of PSUs  =    4791
Number of obs   =    4791
Population size = 71131.726
Design df      =    4785
F( 7, 4779)    =    3.19
Prob > F       =    0.0023
```

f2 owner eq invest 01 0	Coef.	Linearized Std. Err.	t	P> t	[95% Conf. Interval]	
1.g10_gender_owner_01_0	-.0473134	.0933929	-0.51	0.612	-.2304065	.1357796
glbl_hours_owner_01_0	.0077903	.0018915	4.12	0.000	.0040822	.0114985
1.g5_hisp_origin_01_0	-.2241187	.1685798	-1.33	0.184	-.5546126	.1063752
g4_age_owner_01_0	.0055839	.0039507	1.41	0.158	-.0021614	.0133291
1.g6_race_white_01_0	.0370744	.1090216	0.34	0.734	-.1766581	.250807
tot_assets_0	1.39e-08	1.20e-08	1.16	0.247	-9.61e-09	3.74e-08
1.homebased_0	.0379414	.0878312	0.43	0.666	-.1342481	.210131
_cons	.7956481	.2282219	3.49	0.000	.3482282	1.243068

➤ Survival Analysis

```
mi stset Duration [pweight=cswgt_final_0] , failure(event==1)
```

```
      failure event:  event == 1
obs. time interval:  (0, Duration]
exit on or before:  failure
                    weight:  [pweight=cswgt_final_0]
```

```
-----
4928 total obs.
   0 exclusions
-----
```

```
4928 obs. remaining, representing
2190 failures in single record/single failure data
27568 total analysis time at risk, at risk from t =      0
                                     earliest observed entry t =      0
                                     last observed exit t =      8
```

```
sts list if _mi_m==1, survival
```

```
      failure _d:  event == 1
analysis time _t:  Duration
                    weight:  [pweight=cswgt_final_0]
```

Time	Beg. Total	Fail	Net Lost	Survivor Function
1	73278.4	4697	1902	0.9359
2	66679.3	5982	965	0.8519
3	59732.1	5347	1259	0.7757
4	53125.8	5759	1375	0.6916
5	45991.6	4350	1113	0.6262
6	40528	3900	1525	0.5659
7	35103.3	3985	2615	0.5017
8	28503.2	0	2.9e+04	0.5017

```
sts list if _mi_m==0, survival
```

```
      failure _d:  event == 1
analysis time _t:  Duration
                    weight:  [pweight=cswgt_final_0]
```

Time	Beg. Total	Fail	Net Lost	Survivor Function
1	73278.4	4697	1902	0.9359
2	66679.3	5982	965	0.8519
3	59732.1	5347	1259	0.7757
4	53125.8	5759	1375	0.6916
5	45991.6	4350	1113	0.6262
6	40528	3900	1525	0.5659
7	35103.3	3985	2615	0.5017
8	28503.2	0	2.9e+04	0.5017


```

mi estimate: svy: stcox pr_gender_owner_0 pr_race_w_0
pr_hisp_origin_owner_0 m_age_owner_0 pr_native_born_owner_0 tot_assets_0
homebased_0

Multiple-imputation estimates      Imputations      =      5
Survey: Cox regression            Number of obs     =     4928

Number of strata =      6          Population size    = 73278.441
Number of PSUs  =     4928

Average RVI      =     0.0025
Largest FMI      =     0.0066
Complete DF      =     4922
DF adjustment:   Small sample     DF:      min      =     4639.83
                                           avg      =     4822.04
                                           max      =     4919.89
Model F test:    Equal FMI        F( 7, 4912.8)    =     0.67
Within VCE type: Linearized       Prob > F         =     0.7000

-----+-----
          _t |      Coef.  Std. Err.   t    P>|t|    [95% Conf. Interval]
-----+-----
pr_gender_owner_0 | -.0482578   .0565372   -0.85  0.393    -.159096   .0625803
pr_race_w_0       | -.0847179   .066121    -1.28  0.200    -.2143457  .0449099
pr_hisp_origin_owner_0 | .0852772   .1017117    0.84  0.402    -.1141232  .2846776
m_age_owner_0     | .0003172   .0023025    0.14  0.890    -.0041969  .0048313
pr_native_born_owner_0 | .0345032   .0863364    0.40  0.689    -.1347551  .2037614
tot_assets_0      | -1.38e-09   6.55e-09   -0.21  0.833    -1.42e-08  1.15e-08
homebased_0       | -.0470351   .0466294   -1.01  0.313    -.1384496  .0443794
-----+-----

```

6.1.5 Examples - KFS long MI style long

```

use KFS8_Longitudinal_Long_MI_Long,clear
(KFS8 Longitudinal in long format & Multiply Imputed Data in long format)

mi xtset mprid year
      panel variable:  mprid (unbalanced)
      time variable:   year, 2004 to 2011
      delta:           1 unit

mi xeq 0:      xtdescribe

mprid: 10000016, 10000090, ..., 10324611      n =      3140
year:  2004, 2005, ..., 2011                  T =      8
Delta(year) = 1 unit
Span(year)  = 8 periods
(mprid*year uniquely identifies each observation)

Distribution of T_i:  min      5%      25%      50%      75%      95%      max
                    1         1         3         8         8         8         8
Freq.  Percent  Cum. | Pattern
-----+-----
1630   51.91   51.91 | 11111111
303    9.65    61.56 | 1.....
283    9.01    70.57 | 11.....
238    7.58    78.15 | 1111....
224    7.13    85.29 | 111.....
164    5.22    90.51 | 11111...
153    4.87    95.38 | 111111..
145    4.62   100.00 | 1111111.
-----+-----
3140  100.00   | XXXXXXXX

```

```
mi svyset [pweight=wgt_7_long], strata(sampleinfo_samplestrata)
```

```

    pweight: wgt_7_long
           VCE: linearized
Single unit: missing
  Strata 1: sampleinfo_samplestrata
           SU 1: <observations>
           FPC 1: <zero>

```

➤ Regression

```
mi estimate: svy:      reg f24_profitloss_amt tot_assets
pr_gender_owner pr_race_w pr_hisp_origin_owner m_age_owner
pr_native_born_owner i.homebased i.d_education_owner i.year
```

```

Multiple-imputation estimates      Imputations      =      5
Survey: Linear regression          Number of obs    =     18286

Number of strata =      6          Population size   = 408495.43
Number of PSUs  =     18286

Average RVI      =     0.0253
Largest FMI     =     0.0252
Complete DF     =     18280
DF adjustment:  Small sample      DF:      min     =     4725.50
                                           avg     =    14876.49
                                           max     =    18277.99

Model F test:      Equal FMI      F( 14,15295.8) =     4.17
Within VCE type:  Linearized      Prob > F       =     0.0000

```

f24_profitloss_amt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
tot_assets	.0189758	.0169062	1.12	0.262	-.0141619	.0521135
pr_gender_owner	-35698.17	50521.82	-0.71	0.480	-134725.7	63329.38
pr_race_w	47286.26	46706.4	1.01	0.311	-44262.72	138835.2
pr_hisp_origin_owner	-60596.78	35829.83	-1.69	0.091	-130830	9636.444
m_age_owner	-1723.759	1027.937	-1.68	0.094	-3738.612	291.0948
pr_native_born_owner	69215.13	50117.4	1.38	0.167	-29019.69	167449.9
l.homebased	-94632.89	88725.17	-1.07	0.286	-268542.6	79276.77
i.d_education_owner	71605	70967.41	1.01	0.313	-67497.79	210707.8
year						
2005	9401.701	10058.23	0.93	0.350	-10314.16	29117.56
2006	40747.76	13168.15	3.09	0.002	14935.55	66559.96
2007	46025.7	16883.61	2.73	0.006	12932.19	79119.2
2008	34029.68	10851.88	3.14	0.002	12757.12	55302.23
2009	26803.69	11328.97	2.37	0.018	4593.622	49013.76
2010	36590.08	13245.08	2.76	0.006	10627.52	62552.63
2011	554536.9	517519.5	1.07	0.284	-459849.9	1568924
cons	1446.26	57628.8	0.03	0.980	-111511.7	114404.2

```
mi estimate: svy: reg f24_profitloss_amt tot_assets pr_gender_owner
pr_race_w pr_hisp_origin_owner m_age_owner pr_native_born_owner
i.homebased i.d_education_owner i.year , vce(cluster mprid)
```

**option vce() of regress is not allowed with the svy prefix
an error occurred when mi estimate executed svy:regress on m=1**

```
mi estimate: xtgee f24_profitloss_amt tot_assets pr_gender_owner
pr_race_w pr_hisp_origin_owner m_age_owner pr_native_born_owner
i.homebased i.d_education_owner i.year i.sampleinfo_samplestrata
[pweight=wgt_7_long]
```

```
Multiple-imputation estimates      Imputations      =      5
GEE population-averaged model     Number of obs    =     18286

Group variable:                    mprid            Number of groups =     3140
Link:                               identity         Obs per group: min =      1
Family:                             Gaussian         avg =             5.6
Correlation:                        exchangeable     max =             8
Scale parameter:                    x2

Average RVI                        =     0.0284
Largest FMI                        =     0.0304
DF:      min                       =    4459.56
         avg                       =    1.73e+12
         max                       =    3.64e+13
DF adjustment:                     Large sample
Within VCE type:                   Robust          F( 18, .) = .
                                   Prob > F        = .
```

(Within VCE adjusted for clustering on mprid)

f24_profitloss_amt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
tot_assets	.0190176	.0172165	1.10	0.269	-.0147262	.0527613
pr_gender_owner	-130814.2	135291.8	-0.97	0.334	-395981.2	134352.9
pr_race_w	43322.97	42586.63	1.02	0.309	-40145.34	126791.3
pr_hisp_origin_owner	-56046.05	40340.62	-1.39	0.165	-135115	23022.87
m_age_owner	-1574.015	1352.307	-1.16	0.244	-4224.489	1076.459
pr_native_born_owner	77475.11	56675.55	1.37	0.172	-33606.93	188557.1
1.homebased	-93161.77	81828.98	-1.14	0.255	-253543.6	67220.07
1.d_education_owner	70558.25	78073.33	0.90	0.366	-82462.66	223579.2
year						
2005	8349.6	7817.362	1.07	0.286	-6973.857	23673.06
2006	38754.95	10313.37	3.76	0.000	18538.23	58971.66
2007	44068.51	14812.11	2.98	0.003	15037.26	73099.76
2008	32099.43	10403.34	3.09	0.002	11707.15	52491.7
2009	24326.13	10249.35	2.37	0.018	4232.326	44419.94
2010	34260.88	12593.69	2.72	0.007	9576.631	58945.13
2011	551415.6	516541.1	1.07	0.286	-460986.3	1563817
sampleinfo_samplestrata						
102	22023.43	107438.8	0.20	0.838	-188553.3	232600.1
201	-3334.977	83221.16	-0.04	0.968	-166445.7	159775.7
202	152655.7	119241	1.28	0.200	-81052.49	386363.8
301	-21942.74	81839.49	-0.27	0.789	-182345.2	138459.8
302	129366.9	162482.7	0.80	0.426	-189093.5	447827.3
_cons	-41546.75	138386.3	-0.30	0.764	-312779	229685.5

```

mi estimate: xtgee f24_profitloss_amt tot_assets pr_gender_owner
pr_race_w pr_hisp_origin_owner m_age_owner pr_native_born_owner
i.homebased i.d_education_owner i.year i.sampleinfo_samplestrata
[pweight=wgt_7_long] ,vce(robust)

```

```

Multiple-imputation estimates      Imputations      =      5
GEE population-averaged model     Number of obs    =    18286

Group variable:                   mprid            Number of groups =    3140
Link:                             identity          Obs per group: min =      1
Family:                           Gaussian         avg =          5.6
Correlation:                      exchangeable     max =          8
Scale parameter:                  x2

Average RVI                       =    0.0284
Largest FMI                       =    0.0304
DF:      min                      =   4459.56
        avg                       =   1.73e+12
        max                       =   3.64e+13
DF adjustment:                   Large sample
Within VCE type:                 Robust          F( 18, .) = .
                               Prob > F          = .

```

(Within VCE adjusted for clustering on mprid)

f24_profitloss_amt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
tot_assets	.0190176	.0172165	1.10	0.269	-.0147262	.0527613
pr_gender_owner	-130814.2	135291.8	-0.97	0.334	-395981.2	134352.9
pr_race_w	43322.97	42586.63	1.02	0.309	-40145.34	126791.3
pr_hisp_origin_owner	-56046.05	40340.62	-1.39	0.165	-135115	23022.87
m_age_owner	-1574.015	1352.307	-1.16	0.244	-4224.489	1076.459
pr_native_born_owner	77475.11	56675.55	1.37	0.172	-33606.93	188557.1
1.homebased	-93161.77	81828.98	-1.14	0.255	-253543.6	67220.07
1.d_education_owner	70558.25	78073.33	0.90	0.366	-82462.66	223579.2
year						
2005	8349.6	7817.362	1.07	0.286	-6973.857	23673.06
2006	38754.95	10313.37	3.76	0.000	18538.23	58971.66
2007	44068.51	14812.11	2.98	0.003	15037.26	73099.76
2008	32099.43	10403.34	3.09	0.002	11707.15	52491.7
2009	24326.13	10249.35	2.37	0.018	4232.326	44419.94
2010	34260.88	12593.69	2.72	0.007	9576.631	58945.13
2011	551415.6	516541.1	1.07	0.286	-460986.3	1563817
sampleinfo_samplestrata						
102	22023.43	107438.8	0.20	0.838	-188553.3	232600.1
201	-3334.977	83221.16	-0.04	0.968	-166445.7	159775.7
202	152655.7	119241	1.28	0.200	-81052.49	386363.8
301	-21942.74	81839.49	-0.27	0.789	-182345.2	138459.8
302	129366.9	162482.7	0.80	0.426	-189093.5	447827.3
_cons	-41546.75	138386.3	-0.30	0.764	-312779	229685.5

```

mi estimate: xtgee f24_profitloss_amt tot_assets pr_gender_owner
pr_race_w pr_hisp_origin_owner m_age_owner pr_native_born_owner
i.homebased i.d_education_owner i.year i.sampleinfo_samplestrata
[pweight=wgt_7_long] ,vce(robust) corr(ar2)

```

```

Multiple-imputation estimates      Imputations      =      5
GEE population-averaged model    Number of obs    =     17417

Group and time vars:             mprid year      Number of groups =     2554
Link:                             identity         Obs per group: min =      3
Family:                           Gaussian         avg =             6.7
Correlation:                       AR(2)           max =             8
Scale parameter:                   x2

Average RVI                       =     0.0293
Largest FMI                       =     0.0311
DF:      min                      =    4250.25
         avg                      =    1.49e+12
         max                      =    3.14e+13
DF adjustment:                    Large sample
Within VCE type:                  Robust          F( 18, .)       = .
                                Prob > F        = .

```

(Within VCE adjusted for clustering on mprid)

f24_profitloss_amt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
tot_assets	.0190593	.0172152	1.11	0.268	-.0146818	.0528005
pr_gender_owner	-140363.8	144985.1	-0.97	0.333	-424529.4	143801.8
pr_race_w	47302.65	44925.77	1.05	0.292	-40750.27	135355.6
pr_hisp_origin_owner	-67546.9	47845.61	-1.41	0.158	-161325	26231.19
m_age_owner	-1651.657	1440.89	-1.15	0.252	-4475.749	1172.435
pr_native_born_owner	81033.46	61549.75	1.32	0.188	-39601.82	201668.7
1.homebased	-104555.9	88726.17	-1.18	0.239	-278456	69344.19
1.d_education_owner	78165.25	84746.76	0.92	0.356	-87935.35	244265.8
year						
2005	14693.31	7216.369	2.04	0.042	548.1031	28838.51
2006	37866.2	10034.37	3.77	0.000	18196.43	57535.96
2007	43337.13	15158.19	2.86	0.004	13627.61	73046.65
2008	31323.24	10279.84	3.05	0.002	11173.06	51473.43
2009	23462.58	9987.374	2.35	0.019	3882.112	43043.05
2010	33475.91	12369.95	2.71	0.007	9230.315	57721.51
2011	550612.5	516669.3	1.07	0.287	-462040.7	1563266
sampleinfo_samplestrata						
102	28948.57	114731.8	0.25	0.801	-195922.2	253819.3
201	-1745.666	87501.31	-0.02	0.984	-173245.3	169754
202	165904	127408.5	1.30	0.193	-83812.11	415620.2
301	-18729.67	86258.42	-0.22	0.828	-187793.1	150333.8
302	140351.3	174571.1	0.80	0.421	-201801.8	482504.3
_cons	-44675.91	147857.3	-0.30	0.763	-334470.9	245119.1

```
mi estimate: xtreg f24_profitloss_amt tot_assets pr_gender_owner
pr_race_w pr_hisp_origin_owner m_age_owner pr_native_born_owner
i.homebased i.d_education_owner i.year [pweight=wgt_7_long]
fe i(mprid)
```

```
Multiple-imputation estimates      Imputations      =      5
Fixed-effects (within) regression  Number of obs    =    18286
```

```
Group variable: mprid
Number of groups =    3140
Obs per group: min =      1
                  avg =     5.8
                  max =      8
```

```
Average RVI      =    3.5153
Largest FMI      =    0.3841
Complete DF      =    3139
DF: min          =    32.55
    avg          =   2515.01
    max          =   3137.00
```

```
DF adjustment: Small sample
```

```
F( 13, .) = .
Prob > F = .
```

```
Within VCE type: Robust
```

(Within VCE adjusted for 3140 clusters in mprid)

f24_profitloss_amt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
tot_assets	.0206624	.0178933	1.15	0.248	-.0144213	.0557461
pr_gender_owner	-324047.9	261310.7	-1.24	0.215	-836405.6	188309.8
pr_race_w	24317.75	79214.76	0.31	0.759	-131103.4	179738.9
pr_hisp_origin_owner	69976.4	146461.4	0.48	0.636	-228159.1	368111.9
m_age_owner	17675.14	17416.05	1.01	0.310	-16472.86	51823.14
pr_native_born_owner	-117354.7	135703.2	-0.86	0.387	-383588.8	148879.5
l.homebased	-35335.12	21210.76	-1.67	0.097	-77060.77	6390.533
l.d_education_owner	22384.41	68396.98	0.33	0.743	-111723.1	156491.9
year						
2005	-10425.74	18343.58	-0.57	0.570	-46392.59	25541.11
2006	-3225.158	35904.37	-0.09	0.928	-73623.7	67173.38
2007	-15172.64	52031.09	-0.29	0.771	-117191.1	86845.81
2008	-49400.2	69060.9	-0.72	0.474	-184809.3	86008.95
2009	-76011.94	84237.11	-0.90	0.367	-241177.4	89153.51
2010	-87995.17	100528.7	-0.88	0.381	-285104	109113.6
2011	400228.2	412385	0.97	0.332	-408343.7	1208800
_cons	-486096.4	726080	-0.67	0.503	-1909749	937556.2
sigma_u	1223907.7					
sigma_e	4887936.4					
rho	.05899794	(fraction of variance due to u i)				

Note: sigma u and sigma e are combined in the original metric.

```
mi estimate: xtreg f24_profitloss_amt tot_assets pr_gender_owner
pr_race_w pr_hisp_origin_owner m_age_owner pr_native_born_owner
i.homebased i.d_education_owner i.year [pweight=wtg_7_long] ,
fe i(mprid) vce(robust)
```

```
Multiple-imputation estimates      Imputations      =      5
Fixed-effects (within) regression  Number of obs    =    18286

Group variable: mprid              Number of groups  =    3140
                                   Obs per group: min =      1
                                   avg      =     5.8
                                   max      =      8

                                   Average RVI      =    3.5153
                                   Largest FMI       =    0.3841
                                   Complete DF        =    3139
                                   DF: min           =    32.55
                                   avg              =   2515.01
                                   max              =   3137.00

DF adjustment: Small sample        F( 13, .)        =      .
Within VCE type: Robust            Prob > F          =      .
```

(Within VCE adjusted for 3140 clusters in mprid)

f24_profitloss_amt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
tot_assets	.0206624	.0178933	1.15	0.248	-.0144213	.0557461
pr_gender_owner	-324047.9	261310.7	-1.24	0.215	-836405.6	188309.8
pr_race_w	24317.75	79214.76	0.31	0.759	-131103.4	179738.9
pr_hisp_origin_owner	69976.4	146461.4	0.48	0.636	-228159.1	368111.9
m_age_owner	17675.14	17416.05	1.01	0.310	-16472.86	51823.14
pr_native_born_owner	-117354.7	135703.2	-0.86	0.387	-383588.8	148879.5
i.homebased	-35335.12	21210.76	-1.67	0.097	-77060.77	6390.533
i.d_education_owner	22384.41	68396.98	0.33	0.743	-111723.1	156491.9
year						
2005	-10425.74	18343.58	-0.57	0.570	-46392.59	25541.11
2006	-3225.158	35904.37	-0.09	0.928	-73623.7	67173.38
2007	-15172.64	52031.09	-0.29	0.771	-117191.1	86845.81
2008	-49400.2	69060.9	-0.72	0.474	-184809.3	86008.95
2009	-76011.94	84237.11	-0.90	0.367	-241177.4	89153.51
2010	-87995.17	100528.7	-0.88	0.381	-285104	109113.6
2011	400228.2	412385	0.97	0.332	-408343.7	1208800
_cons	-486096.4	726080	-0.67	0.503	-1909749	937556.2
sigma_u	1223907.7					
sigma_e	4887936.4					
rho	.05899794	(fraction of variance due to u i)				

Note: sigma_u and sigma_e are combined in the original metric.

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Appendix A: Percentage of soft missing values

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
b1_bus_start	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
c1z2_legal_status	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
c2_owners	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
c3a_owner_operators	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
c4_numowners_confirm	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
c5_num_employees	2.13	1.15	1.09	0.86	0.15	0.42	0.24	0.35
c6_num_ft_employees	2.41	3.63	3.60	3.81	3.03	2.57	2.40	2.74
c7_num_pt_employees	2.86	4.80	4.63	5.49	3.84	4.86	3.95	3.99
c8_primary_loc	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
c9_loc_change_reason		0.00	0.82	18.71	0.00	0.00	4.55	0.00
c10_morelocations			0.12	0.17	0.15	0.29	0.19	0.35
c11_num_locations			0.27	0.21	0.23	0.50	0.24	0.40
c12a_sba					0.42			
c12b_fed_gov					0.65			
c12c_statelocal_gov					0.58			
c12d_non_profit					0.50			
c12e_college_univ					0.58			
c12f_chamber_of_comm					0.54			
c12g_for_profit_org					0.50			
c12h_other					1.69			
d1a_provide_service	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
d1b_provide_product	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
d1_a_new_product						0.12	0.19	0.10
d1d_new_processes						0.33	0.19	0.20
d1_b_new_to_market						0.75	1.29	0.72
d1c_a_regional						11.82	2.38	1.59
d1c_b_national						8.18	2.38	1.59
d1c_c_international						13.03	2.72	1.59
d2_comp_advantage	1.42	0.60	0.44	0.69	0.35	0.21	0.19	0.10
d2a_compadv_comp_reason				5.44	1.00	0.93	0.81	0.91
d2a_compadv_govlab_reason				5.55	1.20	0.84	1.11	1.14
d2a_compadv_patents_reason				5.44	1.46	1.09	1.11	1.14
d2a_compadv_univ_reason				5.44	1.13	0.76	1.01	0.80
d2b_compadv_comp_strength				18.30	3.55	2.93	3.10	4.23
d2b_compadv_govlab_strength				66.89	30.51	19.61	22.92	26.19
d2b_compadv_patents_strength				38.96	15.49	13.79	12.77	12.36
d2b_compadv_univ_strength				44.09	16.19	8.74	13.64	10.53
d2c_compadv_cost_reason						1.94		
d2c_compadv_design_reason						1.94		
d2c_compadv_expertise_reason						1.68		
d2c_compadv_marketing_reason						2.19		
d2c_compadv_price_reason						1.43		

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
d2c_compadv_reputation_reason						1.94		
d2c_compadv_speed_reason						2.19		
d2d_compadv_cost_strength						4.98		
d2d_compadv_design_strength						3.98		
d2d_compadv_expertise_strength						3.14		
d2d_compadv_marketing_strength						6.32		
d2d_compadv_price_strength						8.59		
d2d_compadv_reput_strength						3.72		
d2d_compadv_speed_strength						4.82		
d3_a_have_patent	0.63	1.48	1.45	1.10	0.50	0.37	0.56	0.40
d3_a_num_patent	0.79	1.93	1.77	1.37	0.96	0.83	0.99	0.90
d3_b_have_copyright	0.71	1.40	1.39	1.23	0.58	0.66	0.85	0.95
d3_b_num_copyright	1.18	3.05	2.65	2.40	2.38	2.91	2.63	2.29
d3_c_have_trademark	0.53	1.03	0.94	1.06	0.46	0.71	0.52	0.55
d3_c_num_trademark	1.22	3.03	3.24	2.64	3.57	3.36	2.45	2.24
d4_a_lic_out_patent	0.69	1.50	1.45	1.10	0.50	0.37	0.56	0.45
d4_b_lic_out_copyright	0.77	1.43	1.42	1.27	0.65	0.66	0.85	0.95
d4_c_lic_out_trademark	0.63	1.03	1.00	1.10	0.54	0.75	0.56	0.55
d5_a_lic_in_patent	0.53	1.08	0.80	0.79	0.77	0.96	0.80	0.80
d5_b_lic_in_copyright	0.61	0.78	0.74	0.58	0.61	0.46	0.42	0.60
d5_c_lic_in_trademark	0.67	0.83	0.86	0.69	0.81	1.04	1.08	0.90
d5a_founded_newprod						0.21		
d5b_a_personaluse						1.15		
d5b_b_previousjob						1.47		
d5b_c_startingbus						1.31		
d6_have_sales	0.18	0.13	0.24	0.00	0.12	0.08	0.14	0.05
d7_perc_sales_bus	0.51	0.25	0.35	0.58	0.27	0.25	0.28	0.05
d7_perc_sales_govt	0.51	0.38	0.35	0.72	0.27	0.29	0.24	0.05
d7_perc_sales_indiv	0.49	0.28	0.32	0.10	0.27	0.25	0.24	0.05
d8_customer_locations				0.41	0.21	0.14	0.21	0.05
d8a_international_sales				0.48	0.33	0.18	0.42	0.05
d8b_perc_international_sales				3.12	2.15	1.04	2.96	0.62
d9_internet_sales				0.74	0.33	0.28	0.42	0.11
d9a_perc_internet_sales				3.28	1.25	1.08	1.86	0.43
e1_a_num_human_res	1.39	0.86	0.83	0.65	0.68	0.70	0.74	0.71
e1_b_num_sales	1.39	0.79	0.75	0.60	0.68	0.70	0.74	0.86
e1_c_num_exec_admin	1.36	0.82	0.79	0.60	0.74	0.70	0.89	0.79
e1_d_num_resdev	1.36	0.86	0.87	0.60	0.91	0.70	0.89	0.79
e1_e_num_prod_manu	1.42	0.93	0.79	0.60	0.85	0.76	0.89	0.79
e1_f_num_gen_admin	1.36	0.75	0.75	0.60	0.85	0.82	0.89	0.86
e1_g_num_fin_admin	1.36	0.82	0.87	0.60	0.85	0.70	0.89	0.86
e1_h_num_other	1.85	1.20	1.03	0.65	1.47	1.20	1.19	1.02
e2a_ft_emp_bonus_plan	1.20	0.31	0.28	0.30	0.57	0.70	0.96	1.18

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
e2a_ft_emp_flex_time	1.26	0.31	0.28	0.20	0.57	0.63	0.59	0.63
e2a_ft_emp_hlth_plan	1.33	0.14	0.12	0.20	0.51	0.44	0.37	0.63
e2a_ft_emp_other	1.13	0.41	0.20	0.40	0.68	1.65	1.85	2.12
e2a_ft_emp_paid_sick	1.36	0.21	0.12	0.40	0.85	0.57	0.67	0.71
e2a_ft_emp_paid_vaca	1.33	0.21	0.36	0.30	0.57	0.63	0.52	0.79
e2a_ft_emp_retire_plan	1.20	0.10	0.16	0.25	0.57	0.51	0.44	0.63
e2a_ft_emp_stock_own	1.30	0.14	0.32	0.30	0.62	1.14	1.19	1.89
e2a_ft_emp_tuit_reim	1.39	0.24	0.16	0.35	0.68	0.82	0.89	0.63
e2b_pt_emp_bonus_plan	14.09	14.32	13.05	15.41	10.14	13.61	11.38	12.93
e2b_pt_emp_flex_time	14.09	14.25	13.28	15.23	10.14	13.03	11.38	11.82
e2b_pt_emp_hlth_plan	14.00	14.25	12.98	14.97	10.04	13.15	11.13	11.96
e2b_pt_emp_other	13.90	14.25	13.13	15.23	10.04	13.84	11.88	14.05
e2b_pt_emp_paid_sick	14.09	14.38	13.05	15.32	10.14	13.03	11.25	12.38
e2b_pt_emp_paid_vaca	14.09	14.32	13.05	15.41	9.94	13.03	11.13	12.10
e2b_pt_emp_retire_plan	14.09	14.18	12.82	15.15	10.04	13.15	11.00	11.96
e2b_pt_emp_stock_own	14.18	14.11	13.21	15.15	10.14	13.61	11.38	12.52
e2b_pt_emp_tuit_reim	14.09	14.25	13.13	14.97	9.94	13.61	11.88	12.24
owner_active	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
f2_owner_eq_invest	0.76	0.84	0.79	0.33	0.35	0.32	0.47	0.32
f2_owner_amt_eq_invest	12.12	3.69	1.88	1.22	0.99	0.94	0.74	0.82
tot_equity_owner_r	3.96	1.59	1.27	0.48	0.46	0.41	0.61	0.61
f2_ownr_amt_eqinvest_all yrs	12.12	7.51	5.30	3.17	2.95	3.36	2.64	3.14
tot_equity_all yrs_owner_r	3.96	2.19	1.74	0.69	0.64	1.20	0.61	1.04
f2_owner_perc_own	1.11	1.41	0.55	0.24	0.48	0.61	0.17	0.11
f6_perc_owned_owner	1.02	1.27	0.50	0.21	0.43	0.53	0.15	0.10
g1a_emp_owner	0.63	1.44	0.73	0.29	0.35	0.47	0.10	0.18
g1b_hours_owner	2.02	3.51	1.70	0.91	1.10	1.20	0.91	0.46
total_hours_owner_r	0.57	1.53	0.61	0.12	0.40	0.29	0.07	0.18
g2_work_exp_owner	0.33	0.48	0.34	0.21	0.19	0.18	0.00	0.18
g3a_oth_bus_owner	0.63	0.63	0.42	0.26	0.21	0.20	0.03	0.29
g3b_bus_same_ind_owner	1.46	1.49	1.01	0.62	0.52	0.49	0.08	0.68
g4_age_owner	0.82	0.77	0.57	0.57	0.54	0.58	0.14	0.21
age_owner_r	0.38	0.60	0.45	0.31	0.29	0.26	0.07	0.14
g5_hisp_origin_owner	0.36	0.50	0.36	0.26	0.24	0.20	0.07	0.14
g6_race_amind_owner	0.41	0.48	0.34	0.29	0.24	0.18	0.07	0.18
g6_race_asian_owner	0.41	0.48	0.34	0.29	0.24	0.18	0.07	0.18
g6_race_black_owner	0.41	0.48	0.34	0.29	0.24	0.18	0.07	0.18
g6_race_nathaw_owner	0.41	0.48	0.34	0.29	0.24	0.18	0.07	0.18
g6_race_other_owner	0.41	0.48	0.34	0.29	0.24	0.18	0.07	0.18
g6_race_white_owner	0.41	0.45	0.34	0.29	0.24	0.18	0.07	0.18
g6b_race_group	0.41	0.45	0.34	0.29	0.24	0.18	0.07	0.18
g7_native_born_owner	0.28	0.55	0.40	0.31	0.24	0.18	0.07	0.18
g8_us_cit_owner	0.25	0.46	0.36	0.21	0.16	0.12	0.03	0.14

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
g9_education_owner	0.64	0.67	0.38	0.17	0.19	0.20	0.07	0.18
g10_gender_owner	0.19	0.55	0.38	0.38	0.38	0.32	0.07	0.07
g10b_marital_status					0.04	0.08	0.09	0.00
g10c_net_worth					0.50	0.42	0.38	0.35
g10d_personal_outlook					0.50			
g1b2_reasonfor_business								0.35
respondent	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
f3_eq_invest_angels	1.02	0.67	0.37	0.21	0.08	0.39	0.09	1.16
f4_eq_amt_angels	2.25	1.06	0.50	0.41	0.30	0.39	0.18	1.16
tot_equity_angels_r	1.62	0.73	0.43	0.34	0.23	0.39	0.18	1.16
f4_eq_amt_angels_all yrs	2.25	1.48	0.63	0.40	0.12	0.68	0.32	2.29
tot_equity_angels_all yrs_r	1.62	1.30	0.47	0.30	0.12	0.68	0.32	2.29
f5_perc_owned_angels	1.23	0.86	0.47	0.40	0.12	0.68	0.16	2.29
f3_eq_invest_companies	0.77	0.67	0.37	0.28	0.38	0.85	0.70	1.07
f4_eq_amt_companies	1.45	0.95	0.56	0.69	0.83	1.09	0.70	1.07
tot_equity_companies_r	0.94	0.73	0.56	0.55	0.75	1.09	0.70	1.07
f4_eq_amt_companies_all yrs	1.45	1.44	0.84	0.58	0.81	1.46	1.25	2.08
tot_equity_companies_all yrs_r	0.94	1.38	0.84	0.39	0.58	1.46	1.25	2.08
f5_perc_owned_companies	0.94	0.90	0.61	0.39	0.70	1.46	1.25	2.08
f3_eq_invest_govt	0.72	0.45	0.68	0.48	0.30	0.54	0.53	0.89
f4_eq_amt_govt	0.81	0.50	0.68	0.55	0.30	0.54	0.53	0.89
tot_equity_govt_r	0.77	0.45	0.68	0.48	0.30	0.54	0.53	0.89
f4_eq_amt_govt_all yrs	0.81	0.47	0.81	0.74	0.46	0.91	0.90	1.67
tot_equity_govt_all yrs_r	0.77	0.47	0.81	0.65	0.46	0.91	0.90	1.67
f5_perc_owned_govt	0.72	0.47	0.81	0.74	0.46	0.91	0.90	1.67
f3_eq_invest_other	0.89	0.78	0.74	0.69	0.83	1.01	0.88	1.61
f4_eq_amt_other	1.15	0.84	0.74	0.76	0.90	1.01	0.88	1.61
tot_equity_other_r	0.94	0.84	0.74	0.76	0.90	1.01	0.88	1.61
f4_eq_amt_other_all yrs	1.15	0.94	0.96	1.02	1.34	1.79	1.53	3.04
tot_equity_other_all yrs_r	0.94	0.94	0.96	1.02	1.34	1.79	1.53	3.04
f5_perc_owned_other	0.81	0.82	0.96	1.02	1.34	1.67	1.53	3.04
f3_eq_invest_parents	1.02	0.67	0.37	0.34	0.15	0.31	0.62	1.16
f4_eq_amt_parents	1.70	1.12	0.56	0.41	0.15	0.31	0.62	1.16
tot_equity_parents_r	1.23	0.95	0.50	0.34	0.15	0.31	0.62	1.16
f4_eq_amt_parents_all yrs	1.70	1.29	0.70	0.59	0.24	0.55	1.14	2.34
tot_equity_parents_all yrs_r	1.23	1.23	0.62	0.49	0.24	0.55	1.14	2.34
f5_perc_owned_parents	1.19	0.92	0.47	0.59	0.24	0.55	1.14	2.34
f3_eq_invest_spouse	1.06	0.56	0.31	0.21	0.15	0.47	0.26	0.80
f4_eq_amt_spouse	1.62	0.78	0.31	0.21	0.23	0.47	0.35	0.80
tot_equity_spouse_r	1.32	0.67	0.31	0.21	0.23	0.47	0.35	0.80
f4_eq_amt_spouse_all yrs	1.62	0.78	0.46	0.29	0.35	0.92	0.62	1.54
tot_equity_spouse_all yrs_r	1.32	0.72	0.38	0.29	0.35	0.79	0.47	1.54
f5_perc_owned_spouse	1.19	0.72	0.46	0.29	0.23	0.79	0.47	1.54

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
f3_eq_invest_vent_cap	0.94	0.56	0.56	0.48	0.08	0.39	0.26	0.89
f4_eq_amt_vent_cap	1.36	0.67	0.62	0.55	0.15	0.47	0.26	0.89
tot_equity_vent_cap_r	1.19	0.67	0.62	0.48	0.08	0.39	0.26	0.89
f4_eq_amt_vent_cap_all yrs	1.36	0.71	0.74	0.74	0.23	0.77	0.45	1.67
tot_equity_vent_cap_all yrs_r	1.19	0.71	0.74	0.65	0.23	0.64	0.45	1.67
f5_perc_owned_vent_cap	1.15	0.65	0.74	0.74	0.11	0.64	0.45	1.67
f5a_seek_equity						0.50	0.05	0.10
f6a_personal_use	20.21	0.30	0.29	0.24	0.35	0.58	0.19	0.45
f6b_personal_use_amt	20.21	1.85	1.03	0.93	0.81	1.12	0.56	1.15
tot_personal_use_r	20.21	1.85	0.62	0.34	0.46	0.75	0.24	0.75
f6z_family_owned					18.04			
f7a_bus_credcard	0.93	0.50	0.44	0.55	0.42	0.66	0.52	0.55
f7b_bus_credcard_numused	2.56	3.78	4.13	4.32	8.60	7.81	7.90	7.57
f8a_bus_credcard_line	2.86	2.07	1.81	1.78	1.37	1.77	1.77	1.85
tot_bus_credcard_line_resp_r	1.50	1.03	0.90	1.13	0.71	1.24	1.31	1.11
f8b_bus_credcard_bal	2.19	1.84	1.45	1.31	0.93	1.50	1.31	1.38
tot_bus_credcard_bal_resp_r	1.58	1.03	0.80	0.89	0.66	1.11	1.15	1.11
f7a_pers_credcard	1.01	0.53	0.83	0.65	0.54	0.54	0.61	0.90
f7b_pers_credcard_numused	2.76	2.33	2.74	2.71	4.60	5.27	5.17	4.78
f8a_pers_credcard_line	4.18	2.85	2.52	2.36	1.43	1.81	1.90	2.52
tot_pers_credcard_line_resp_r	2.25	1.41	1.62	1.48	1.17	1.21	1.71	2.09
f8b_pers_credcard_bal	4.26	2.57	2.52	2.09	1.37	1.28	2.19	2.52
tot_pers_credcard_bal_resp_r	2.19	1.28	1.75	1.15	0.98	1.21	1.62	2.09
f7a_pers_loan_bank	1.10	0.48	0.56	0.51	0.61	0.62	0.47	0.65
f7b_pers_loan_bank_numused	2.05	1.25	1.56	1.54	2.03	2.08	1.60	1.94
f8c_pers_loan_bank_amt	2.62	0.90	0.91	1.17	1.23	1.37	0.56	0.90
tot_pers_loan_bank_resp_r	1.56	0.63	0.71	0.99	1.07	1.25	0.52	0.80
f8d_pers_loan_bank_owed	2.62	1.35	1.35	1.13	1.20	1.22	0.99	1.79
tot_pers_loan_bank_owed_resp_r	1.56	1.35	1.06	0.75	1.08	1.15	0.91	1.51
f7a_pers_loan_fam	0.91	0.70	0.88	0.55	0.46	1.00	0.56	0.75
f7b_pers_loan_fam_numused	1.54	1.50	1.50	1.20	1.61	2.45	1.74	1.84
f8c_pers_loan_fam_amt	1.46	0.95	0.97	0.75	0.65	1.04	0.66	0.80
tot_pers_loan_fam_resp_r	1.14	0.78	0.91	0.62	0.58	1.04	0.61	0.75
f8d_pers_loan_fam_owed	1.46	1.05	1.16	0.99	0.61	1.47	0.98	1.27
tot_pers_loan_fam_owed_resp_r	1.14	1.05	1.09	0.73	0.61	1.47	0.91	1.19
f7a_pers_loan_other	0.91	0.63	0.71	0.51	0.50	0.83	0.38	0.85
f7b_pers_loan_other_numused	1.16	0.95	0.91	0.65	0.77	1.37	0.80	1.44
f8c_pers_loan_other_amt	1.03	0.78	0.77	0.58	0.58	1.00	0.38	0.85
tot_pers_loan_other_resp_r	0.93	0.73	0.74	0.51	0.50	0.96	0.38	0.85
f8d_pers_loan_other_owed	1.03	0.77	0.82	0.67	0.65	1.06	0.49	1.25
tot_persloan_other_owed_resp_r	0.93	0.77	0.76	0.59	0.60	1.06	0.49	1.18
f7a_pers_other	1.75	1.63	1.24	1.48	1.27	1.74	1.13	1.30
f7b_pers_other_numused	1.95	1.75	1.33	1.58	1.46	2.08	1.36	1.44

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
f8c_pers_other_amt	1.81	1.63	1.30	1.51	1.30	1.74	1.13	1.30
tot_pers_other_resp_r	1.66	1.63	1.27	1.48	1.27	1.74	1.13	1.30
f8d_pers_other_owed	1.81	1.67	1.45	1.81	1.63	2.33	1.56	1.90
tot_pers_other_owed_resp_r	1.66	1.67	1.41	1.72	1.58	2.33	1.56	1.90
f9a_bus_credcard	1.75	1.65	1.33	0.21	3.33	3.06	2.98	3.96
f9b_bus_credcard_numused	2.43	3.60	2.30	2.04	6.53	5.42	5.96	7.92
f10a_bus_credcard_line	2.97	2.98	2.66	1.63	6.83	7.18	6.96	10.68
tot_bus_credcard_line_others_r	2.36	2.33	2.39	0.72	6.38	6.35	6.59	10.26
f10b_bus_credcard_bal	2.83	2.79	2.39	1.45	6.61	7.18	6.59	10.26
tot_bus_credcard_bal_others_r	2.43	2.33	2.26	0.36	6.38	6.35	6.59	10.26
f9a_pers_credcard	2.16	2.03	1.51	0.54	3.45	3.34	3.31	4.13
f9b_pers_credcard_numused	3.03	2.93	2.22	1.29	5.30	5.42	4.14	5.51
f10a_pers_credcard_line	6.14	4.37	3.39	3.09	7.04	8.00	8.37	11.76
tot_pers_credcard_line_others_r	3.44	3.28	2.97	1.55	6.80	6.86	7.97	10.86
f10b_pers_credcard_bal	4.99	3.97	3.53	1.55	7.04	7.71	7.97	11.31
tot_pers_credcard_bal_others_r	3.64	2.98	2.97	0.97	6.80	6.86	7.97	11.31
f9a_pers_loan_bank	2.36	1.65	1.24	0.21	3.69	3.20	2.98	4.48
f9b_pers_loan_bank_numused	2.83	2.18	1.51	0.75	4.43	3.76	3.31	5.34
f10c_pers_loan_bank_amt	3.03	1.88	1.42	0.43	3.82	3.20	2.98	4.99
tot_pers_loan_bank_others_r	2.76	1.73	1.33	0.21	3.82	3.20	2.98	4.82
f10d_pers_loan_bank_owed	3.03	2.39	2.26	0.90	6.74	6.30	6.27	11.37
tot_persloan_bank_owed_others_r	2.76	2.39	2.00	0.36	6.52	6.30	6.27	10.98
f9a_pers_loan_fam	2.16	2.03	1.86	1.18	3.69	3.48	3.15	4.48
f9b_pers_loan_fam_numused	2.43	2.18	1.95	1.29	4.19	3.62	3.15	4.65
f10c_pers_loan_fam_amt	2.16	2.18	1.86	1.18	3.82	3.48	3.15	4.82
tot_persloan_fam_othrowners_r	2.16	2.03	1.86	1.18	3.69	3.48	3.15	4.82
f10d_pers_loan_fam_owed	2.16	2.53	2.59	1.82	6.02	6.27	6.07	9.64
tot_persloan_fam_owed_others_r	2.16	2.53	2.59	1.82	6.02	6.27	6.07	9.64
f9a_pers_loan_other	1.82	1.80	1.51	0.54	3.69	3.20	3.15	3.96
f9b_pers_loan_other_numused	1.82	1.88	1.68	0.54	3.69	3.34	3.15	4.13
f10c_pers_loan_other_amt	1.89	1.80	1.51	0.54	3.69	3.20	3.15	3.96
tot_pers_loan_other_owners_r	1.89	1.80	1.51	0.54	3.69	3.20	3.15	3.96
f10d_pers_loan_other_owed	1.89	2.14	2.05	0.82	5.84	5.56	5.86	8.10
tot_persloan_othr_owed_others_r	1.89	2.14	2.05	0.82	5.84	5.56	5.86	8.10
f9a_pers_other	2.16	2.18	1.33	1.07	3.82	3.89	3.64	4.82
f9b_pers_other_numused	2.16	2.25	1.33	1.07	4.06	4.03	3.64	5.16
f10c_pers_other_amt	2.16	2.18	1.42	1.07	3.82	3.89	3.64	4.82
tot_pers_other_other_owners_r	2.16	2.18	1.42	1.07	3.82	3.89	3.64	4.82
f10d_pers_other_owed	2.16	2.59	1.83	1.63	6.07	6.83	6.90	10.00
tot_pers_other_owed_others_r	2.16	2.59	1.83	1.63	6.07	6.83	6.90	10.00
f11a_bus_cred_line	0.83	0.58	0.47	0.62	0.73	0.83	0.42	0.85
f11b_bus_cred_line_numused	1.38	1.60	1.89	1.68	3.95	4.11	3.95	3.99
f12a_bus_cred_line	1.28	0.89	1.03	1.18	1.44	1.40	0.89	2.03

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
tot_cred_line_bus_line_r	0.99	0.71	0.63	0.80	1.10	1.22	0.76	1.64
f12b_bus_cred_line_bal	1.48	0.94	1.06	1.44	1.24	1.45	0.82	1.95
tot_cred_line_bus_bal_r	0.99	0.76	0.73	0.80	1.05	1.28	0.69	1.64
f11a_bus_credcard	0.63	0.38	0.65	0.62	0.96	1.16	0.33	0.60
f11b_bus_credcard_numused	1.60	2.58	2.95	2.54	6.14	6.10	4.84	4.68
f12a_bus_credcard_line	2.44	1.72	2.58	2.51	2.37	2.42	1.55	2.17
tot_credcard_line_bus_r	1.36	0.90	1.31	1.20	1.99	2.12	1.01	1.45
f12b_bus_credcard_bal	1.89	1.50	1.97	2.04	2.44	2.71	1.01	1.66
tot_credcard_bal_bus_r	1.20	0.85	1.00	1.05	1.92	2.20	0.82	1.24
f11a_bus_loans_bank	0.79	0.75	0.65	0.69	0.58	1.12	0.80	1.05
f11b_bus_loans_bank_numused	1.08	1.25	1.15	1.44	1.30	2.20	1.83	2.04
f12c_bus_loans_bank_amt	1.54	0.93	1.18	1.17	0.73	1.20	0.94	1.20
tot_loan_bank_bus_r	1.08	0.80	0.88	0.86	0.58	1.12	0.89	1.10
f12d_bus_loans_bank_owed	1.54	1.05	1.16	1.17	0.91	1.68	1.44	1.86
tot_bus_loans_bank_owed_r	1.08	1.05	0.90	0.88	0.76	1.57	1.37	1.70
f11a_bus_loans_nonbank	0.71	0.58	0.50	0.65	0.77	0.79	0.61	0.65
f11b_bus_loans_nonbank_numused	0.77	0.73	0.59	0.79	1.11	1.12	0.89	0.80
f12c_bus_loans_nonbank_amt	0.85	0.65	0.59	0.79	0.77	0.87	0.66	0.75
tot_loan_nonbank_bus_r	0.77	0.60	0.53	0.69	0.77	0.83	0.66	0.65
f12d_bus_loans_nonbank_owed	0.85	0.72	0.60	0.83	0.94	1.13	1.00	0.98
tot_bus_loans_nonbank_owed_r	0.77	0.72	0.54	0.75	0.94	1.07	0.88	0.91
f11a_bus_loans_emp	5.07	6.89	5.84	7.86	1.81	1.68	0.92	1.25
f11b_bus_loans_emp_numused	5.07	6.93	5.98	7.92	1.95	1.84	1.02	1.25
f12c_bus_loans_emp_amt	5.07	6.89	5.84	7.92	1.81	1.68	1.02	1.25
tot_loan_emp_bus_r	5.07	6.89	5.84	7.86	1.81	1.68	0.92	1.25
f12d_bus_loans_emp_owed	5.07	11.68	12.16	16.93	5.05	4.98	3.24	4.48
tot_bus_loans_emp_owed_r	5.07	11.68	12.16	16.93	5.05	4.98	2.94	4.48
f11a_bus_loans_fam	0.75	0.73	0.50	0.82	0.61	0.87	0.47	0.75
f11b_bus_loans_fam_numused	1.10	1.13	0.77	0.99	1.07	1.50	0.85	1.30
f12c_bus_loans_fam_amt	0.93	0.78	0.53	0.99	0.73	0.87	0.52	0.75
tot_loan_fam_bus_r	0.83	0.78	0.50	0.89	0.69	0.87	0.47	0.75
f12d_bus_loans_fam_owed	0.93	0.80	0.61	1.05	0.86	1.15	0.64	1.07
tot_bus_loans_fam_owed_r	0.83	0.80	0.55	0.97	0.81	1.15	0.64	1.07
f11a_bus_loans_govt	0.89	0.98	0.74	0.86	0.81	0.96	0.61	0.70
f11b_bus_loans_govt_numused	0.97	1.05	0.80	0.86	0.88	1.04	0.66	0.85
f12c_bus_loans_govt_amt	1.01	0.98	0.80	0.89	0.81	1.00	0.71	0.70
tot_loan_govt_bus_r	0.91	0.98	0.80	0.86	0.81	0.96	0.66	0.70
f12d_bus_loans_govt_owed	1.01	1.07	0.79	1.02	0.97	1.27	0.86	0.96
tot_bus_loans_govt_owed_r	0.91	1.07	0.79	0.98	0.97	1.21	0.86	0.96
f11a_bus_loans_other_ind	0.89	0.83	0.68	0.82	0.81	0.83	0.56	1.10
f11b_busloans_otherind_numused	0.99	0.93	0.68	0.86	0.84	1.08	0.71	1.10
f12c_bus_loans_other_ind_amt	0.93	0.90	0.68	0.89	0.81	0.83	0.56	1.10
tot_loan_other_ind_r	0.91	0.85	0.68	0.82	0.81	0.83	0.56	1.10

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
f12d_bus_loans_other_ind_owed	0.93	0.97	0.75	1.01	0.96	1.05	0.73	1.49
tot_bus_loans_otherind_owed_r	0.91	0.97	0.75	0.93	0.96	1.05	0.73	1.49
f11a_bus_loans_owner	0.88	0.88	15.37	18.08	18.25	27.81	27.84	25.49
f11b_bus_loans_owner_numused	1.29	1.76	15.76	18.35	18.86	28.59	28.36	26.19
f12c_bus_loans_owner_amt	1.60	1.07	15.37	18.08	18.25	27.92	27.84	25.49
tot_loan_owner_bus_r	1.34	0.94	15.37	18.08	18.25	27.92	27.84	25.49
f12d_bus_loans_owner_owed	1.60	1.44	18.83	25.32	28.06	42.74	44.92	45.16
tot_bus_loans_owner_owed_r	1.34	1.36	18.83	25.32	28.06	42.74	44.92	45.16
f11a_bus_loans_other_bus	0.81	0.73	0.53	0.79	0.73	0.91	0.52	0.75
f11a_busloans_otherbus_numused	0.87	0.78	0.59	0.79	0.77	0.96	0.66	0.80
f12c_bus_loans_bus_amt	0.85	0.75	0.53	0.79	0.73	0.96	0.52	0.75
tot_loan_other_bus_r	0.83	0.75	0.53	0.79	0.73	0.96	0.52	0.75
f12d_bus_loans_bus_owed	0.85	0.79	0.56	0.89	0.87	1.15	0.67	1.02
tot_bus_loans_otherbus_owed_r	0.83	0.79	0.56	0.89	0.87	1.15	0.67	1.02
f11a_bus_other	1.01	1.10	0.80	1.20	1.38	1.58	0.85	1.49
f11b_bus_other_numused	1.08	1.25	0.88	1.23	1.50	1.70	0.85	1.54
f12c_bus_other_amt	1.06	1.13	0.91	1.27	1.38	1.58	0.85	1.49
tot_bus_debt_other_r	1.03	1.13	0.88	1.23	1.38	1.58	0.85	1.49
f12d_bus_other_owed	1.06	1.12	0.85	1.41	1.67	2.03	1.12	2.08
tot_bus_loans_other_owed_r	1.03	1.12	0.85	1.37	1.67	2.03	1.12	2.08
f12e_collateral						1.03	0.27	0.45
f12f_bus_real_estate						6.91	3.36	2.96
f12f_business_equip_veh						6.25	2.94	3.45
f12f_business_sec_dep						6.25	2.52	3.45
f12f_intellectual_prop						6.58	2.52	3.45
f12f_inventory_acctrec						6.25	3.36	3.45
f12f_other						6.25	2.52	2.96
f12f_other_pers_assets						5.92	2.10	3.94
f12f_pers_real_estate						6.58	2.94	3.94
f13_trade_fin	0.43	0.45	0.59	0.27	0.27	0.37	0.09	0.65
f14a_trade_fin_amt	3.35	2.03	1.47	1.06	0.92	1.00	0.61	1.10
tot_trade_finan_r	0.85	0.70	0.62	0.31	0.27	0.50	0.24	0.80
f14d_new_loans				0.27	0.27	0.37	0.09	0.35
f14g_didnotapply				0.14	0.23	0.42	0.19	0.40
f14h_loan_guarantees					0.27	0.33	0.09	0.25
f14e_approved_denied				0.28	0.29	0.00	0.00	0.00
f14f_bus_credit_hist				11.01	6.84	12.07	4.71	17.14
f14f_inadeq_doc				11.01	8.55	11.21	7.06	18.57
f14f_insuff_coll				10.09	8.55	12.07	3.53	20.00
f14f_loan_toolarge				11.01	10.26	11.21	3.53	18.57
f14f_new_bus				11.93	9.40	12.07	7.06	18.57
f14f_other				11.01	8.55	12.93	5.88	20.00
f14f_pers_credit_hist				11.01	8.55	12.07	3.53	18.57

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
f14f_restr_on_lending					90.60	7.76	2.35	14.29
f14i_economy_effect					0.23			
f14j_most_challenging					1.53	1.62	1.51	1.79
f15_revenue	0.73	0.78	0.65	0.27	0.19	0.46	0.24	0.15
f16a_rev_amt	12.62	7.20	3.66	3.26	9.02	3.65	2.40	2.94
tot_revenue_r	3.79	2.00	1.42	0.93	6.83	1.45	0.66	0.90
f17a_total_exp_amt	16.54	9.88	4.90	4.08	3.53	3.28	2.59	2.89
tot_expenses_r	4.10	2.00	1.12	0.65	0.58	1.00	0.52	1.10
f18a_wage_exp_amt	8.28	5.88	4.22	3.16	1.92	2.28	1.88	2.09
tot_wages_r	4.36	2.65	2.12	1.48	0.46	1.00	0.61	1.20
f19_res_dev	0.39	0.38	0.29	0.31	0.15	0.17	0.05	0.30
f19a_res_dev_amt				0.86	0.81	0.87	0.52	0.60
tot_res_dev_r				0.38	0.27	0.37	0.14	0.40
f19b_a_design					0.44	0.99	0.96	1.60
f19b_b_investments					0.65	1.72	2.23	1.60
f19b_c_brand_dev					1.09	1.72	0.96	1.60
f19b_d_org_dev					0.65	1.72	1.27	1.60
f19b_e_worker_training					1.09	1.72	0.64	1.92
f19b_f_other					2.18	2.46	3.50	4.79
f19c_a_design_amt						6.77	4.84	4.76
tot_intangassets_design_r						2.90	1.61	2.78
f19c_b_investments_amt						10.84	8.81	4.67
tot_intangassets_invest_r						5.91	4.40	3.33
f19c_c_brand_dev_amt						9.17	6.57	5.49
tot_intangassets_branddev_r						5.83	2.53	3.85
f19c_d_org_dev_amt						13.75	9.09	9.21
tot_intangassets_orgdev_r						11.25	6.49	6.58
f19c_e_worker_training_amt						11.18	4.84	7.96
tot_intangassets_wkrtrng_r						6.58	2.42	6.19
f19c_f_other_amt						75.00	68.75	75.00
tot_intangassets_other_r						68.75	68.75	75.00
f19c_intangassets_amt					14.81			
tot_intang_assets_r					1.09			
f20_mach	0.47	0.73	0.62	0.48	0.27	0.54	0.61	0.25
f21_land_rent	0.45	0.58	0.59	0.41	0.35	0.42	0.47	0.55
f22_mach_rent	0.45	0.68	0.59	0.55	0.19	0.33	0.24	0.40
f23_profit_or_loss	2.70	1.93	1.24	0.51	0.38	1.04	0.89	1.10
f24_profit_amt	16.80	9.17	6.13	4.97	3.42	5.15	4.01	4.96
tot_profit_r	9.75	4.75	2.89	1.62	1.27	2.77	2.08	2.88
f26_loss_amt	19.39	13.60	8.71	7.37	6.17	6.54	6.15	5.95
tot_loss_r	9.05	6.65	4.91	2.19	2.12	3.27	3.21	4.69
f24_profitloss_amt	15.95	9.20	5.87	5.42	4.14	4.69	3.90	4.24
f28a_asset_cash	1.28	0.68	0.53	0.21	0.88	0.42	0.66	0.65

Follow-Up	_0	_1	_2	_3	_4	_5	_6	_7
f29_assetval_cash	11.10	6.65	3.60	2.92	2.84	2.95	2.45	2.99
tot_asset_cash_r	5.03	2.48	1.47	0.82	1.46	1.25	1.27	1.84
f28b_asset_acct_rec	2.03	1.23	1.12	0.72	1.73	1.62	1.08	1.69
f29_assetval_acctrec	8.64	5.35	3.69	2.85	3.42	3.45	2.73	3.44
tot_asset_acct_rec_r	4.71	2.60	1.95	1.30	2.07	1.95	1.55	2.54
f28c_asset_inv	1.10	1.45	1.47	1.27	1.88	1.58	1.51	1.59
f29_assetval_inv	5.19	4.48	2.89	2.81	3.11	3.24	2.73	2.79
tot_asset_inv_r	2.70	2.30	1.80	1.58	2.07	1.99	1.65	2.09
f28d_asset_equip	0.83	0.95	0.74	0.55	1.27	1.29	0.89	1.10
f29_assetval_equip	6.21	4.80	2.80	2.57	2.80	3.16	2.30	2.79
tot_asset_equip_r	2.80	2.00	1.33	0.93	1.65	1.62	1.18	1.69
f28e_asset_landbuild	1.36	2.28	1.92	1.34	2.30	2.24	2.12	1.99
f29_assetval_landbuild	2.31	2.93	2.51	1.85	2.65	2.74	2.35	2.69
tot_asset_landbuild_r	1.77	2.40	2.04	1.44	2.34	2.37	2.12	2.34
f28f_asset_veh	1.18	1.85	1.59	1.27	1.88	2.12	1.65	1.44
f29_assetval_veh	2.56	3.23	2.57	1.89	2.69	2.95	2.40	2.09
tot_asset_veh_r	1.68	2.25	1.95	1.30	2.15	2.28	1.79	1.59
f28g_other_bus_prop	4.30	3.18	2.80	2.54	3.30	3.20	3.10	3.19
f29_assetval_othbusprop	4.44	3.25	2.86	2.71	3.30	3.24	3.20	3.39
tot_asset_other_bus_prop_r	1.77	3.18	2.80	2.57	3.30	3.20	3.15	3.34
f28h_other_assets	3.49	3.23	3.10	2.54	3.30	3.61	3.29	3.49
f29_assetval_other	3.90	3.65	3.45	2.85	3.53	3.90	3.39	3.69
tot_asset_other_r	1.93	3.30	3.22	2.64	3.49	3.61	3.34	3.54
f30a_liab_acctpay	1.46	0.60	0.65	0.48	0.84	0.75	0.42	0.50
f31_value_acctpay	6.03	3.65	2.39	1.92	1.84	2.24	1.46	1.54
tot_liab_acct_pay_r	3.23	1.38	1.09	0.69	1.19	1.04	0.61	0.95
f30b_liab_pension	1.14	1.55	1.24	0.99	1.69	1.29	1.51	1.10
f31_value_pension	1.44	1.80	1.47	1.20	1.77	1.54	1.88	1.20
tot_liab_pension_r	1.28	1.68	1.33	0.99	1.69	1.41	1.60	1.10
f30c_liab_other	1.38	1.93	1.74	1.61	1.96	1.87	1.83	1.79
f31_value_other	1.66	2.05	1.80	1.78	1.96	1.91	1.88	1.94
tot_liab_other_r	1.54	1.98	1.77	1.68	1.96	1.87	1.83	1.84
f32_chap11_bankruptcy					0.27	1.08	0.24	0.25
f33_expected_growth					0.19			
f34_future_revenue					0.77			
respondent	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
website	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
email	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
credrisk	26.83	2.28	13.04	14.48	8.10	16.45	16.56	20.63
fssp	26.87	5.18	5.93	7.41	8.21	16.53	16.60	20.63
paysc	95.70	84.49	76.28	59.18	51.92	49.50	46.71	41.85

Appendix B

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	Yes	Yes	Yes	Yes	Yes	In what calendar year did [NAME BUSINESS] close?	a11_year_closed
No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Did [NAME BUSINESS] file for bankruptcy?	a11a_bankruptcy
No	No	No	No	Yes	No	No	No	How much did the nation's recent financial problems, which became highly visible in YYYY, affect [NAME BUSINESS] during calendar year YYYY? Would you say . . .	a11b_economy_effect
No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Our records show that [NAME BUSINESS] had a legal status of [LEGAL STATUS]. As of December 31, YYYY, is that still the legal status of [NAME BUSINESS]?	c1z_confirm_legal_status
No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	I'm going to read you a list of some different forms of legal status a business can have. As of December 31, YYYY, which form of legal status did [NAME BUSINESS] have? Was it a . . . Something else? (SPECIFY)	c1z2otherspecify
No	Yes	Yes	Yes	No	No	No	No	Was this change an increase, a decrease, or no change in the number of people who worked for [NAME BUSINESS] on December 31, YYYY compared to December 31, YYYY?	c5b_num_employees_change
No	Yes	Yes	Yes	No	No	No	No	And what was the (increase/decrease) in the number of people who worked for [NAME BUSINESS] on December 31, YYYY compared to December 31, YYYY? Your best estimate is fine	c5c_num_employees_change_amt
No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Our records show that the primary location where [NAME BUSINESS] operates is [PRIMARY LOCATION]. Is that correct?	c8z_primary_loc_confirm
No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	What was the main reason for the change of location?	c9_loc_change_reason

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	What was the main reason for the change of location? OTHER (SPECIFY)	c9otherspecify
No	No	Yes	Yes	Yes	Yes	Yes	Yes	As of December 31, YYYY, did [NAME BUSINESS] operate in more than one location?	c10_morelocations
No	No	Yes	Yes	Yes	Yes	Yes	Yes	And as of December 31, YYYY, how many locations did [NAME BUSINESS] operate in?	c11_num_locations
No	No	Yes	Yes	Yes	Yes	Yes	Yes	In what month and year did you open your second location?, Month	c11a_2ndopening_month
No	No	Yes	Yes	Yes	Yes	Yes	Yes	In what month and year did you open your second location?, Year	c11a_2ndopening_year
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - The Small Business Administration or SBA	c12a_sba
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - A Federal government agency other than SBA	c12b_fed_gov

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - A state or local government	c12c_statelocal_gov
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - A non-profit association for small businesses such as SCORE	c12d_non_profit
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - A community college or university	c12e_college_univ
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - A chamber of commerce	c12f_chamber_of_comm

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - A for-profit organization such as an accounting firm	c12g_for_profit_org
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - Another Source	c12h_other
No	No	No	No	Yes	No	No	No	There are many programs available to help new businesses. I am going to read some possible sources of training and assistance that may have been used to help [NAME BUSINESS]. Have you (or any of the other owners) ever received any business training, mentoring, or technical assistance sponsored by (READ ITEM) to help [NAME BUSINESS]? - Other source specify	c12other_specify
No	No	No	No	No	Yes	No	No	As of December 31, YYYY, what state is [NAME BUSINESS] chartered in?	c1z3_state_chartered
No	No	No	No	No	Yes	Yes	Yes	First, during calendar year YYYY, did (BUSINESS NAME) introduce any products or services that were new or significantly improved?	d1_a_new_product
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, were any of the products or services new to any market or markets [NAME BUSINESS] competes in?	d1_b_new_to_market
No	No	No	No	No	Yes	Yes	Yes	Were any of the new or significantly improved products or services introduced in YYYY new to [ITEM]? a) A regional market such as nearby cities or counties	d1c_a_regional

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	No	Yes	Yes	Yes	Were any of the new or significantly improved products or services introduced in YYYY new to [ITEM]? b) A national-wide market	d1c_b_national
No	No	No	No	No	Yes	Yes	Yes	Were any of the new or significantly improved products or services introduced in YYYY new to [ITEM]? c) An international market	d1c_c_international
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, did [BUSINESS NAME] introduce any new or significantly improved processes in the production of goods or providing services? Please include any new or improved processes, even if [NAME BUSINESS] was not the first to introduce it.	d1d_new_processes
No	No	No	Yes	Yes	Yes	Yes	Yes	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to teaming up with another company?	d2a_compadv_comp_reason
No	No	No	Yes	Yes	Yes	Yes	Yes	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to teaming up with a government lab or research center?	d2a_compadv_govlab_reason
No	No	No	Yes	Yes	Yes	Yes	Yes	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to patents that [NAME BUSINESS] owns, has applied for, or licensed?	d2a_compadv_patents_reason
No	No	No	Yes	Yes	Yes	Yes	Yes	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to teaming up with a college or university?	d2a_compadv_univ_reason
No	No	No	Yes	Yes	Yes	Yes	Yes	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY?	d2b_compadv_comp_strength

Appendix B – Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	Yes	Yes	Yes	Yes	Yes	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY?	d2b_compadv_govlab_strength
No	No	No	Yes	Yes	Yes	Yes	Yes	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY?	d2b_compadv_patents_strength
No	No	No	Yes	Yes	Yes	Yes	Yes	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY?	d2b_compadv_univ_strength
No	No	No	No	No	Yes	No	No	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to [ITEM]? e) Cost advantages	d2c_compadv_cost_reason
No	No	No	No	No	Yes	No	No	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to [ITEM]? f) Product or service design or quality	d2c_compadv_design_reason
No	No	No	No	No	Yes	No	No	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to [ITEM]? g) Specialized or range of expertise, products or service	d2c_compadv_expertise_reason
No	No	No	No	No	Yes	No	No	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to [ITEM]? b) Marketing and promotion	d2c_compadv_marketing_reason
No	No	No	No	No	Yes	No	No	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to [ITEM]? a) Price	d2c_compadv_price_reason
No	No	No	No	No	Yes	No	No	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to [ITEM]? d) Established reputation	d2c_compadv_reputation_reason

Appendix B – Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	No	Yes	No	No	Was the competitive advantage [NAME BUSINESS] had in calendar year YYYY related in any way to [ITEM]? c) Speed of service	d2c_compadv_speed_reason
No	No	No	No	No	Yes	No	No	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY? e) Cost advantages	d2d_compadv_cost_strength
No	No	No	No	No	Yes	No	No	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY? f) Product or service design or quality	d2d_compadv_design_strength
No	No	No	No	No	Yes	No	No	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY? g) Specialized or range of expertise, products or service	d2d_compadv_expertise_strength
No	No	No	No	No	Yes	No	No	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY? b) Marketing and promotion	d2d_compadv_marketing_strength
No	No	No	No	No	Yes	No	No	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY? a) Price	d2d_compadv_price_strength
No	No	No	No	No	Yes	No	No	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY? d) Established reputation	d2d_compadv_reput_strength
No	No	No	No	No	Yes	No	No	Do you consider this to have given [NAME BUSINESS] a major or a minor competitive advantage in calendar year YYYY? c) Speed service	d2d_compadv_speed_strength
No	No	No	No	No	Yes	No	No	Was [NAME BUSINESS] founded around a new or customized product or service that was created by you or one of the founders of the business?	d5a_founded_newprod

Appendix B – Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	No	Yes	No	No	Thinking about the new or customized product or service, around which [NAME BUSINESS] was founded, why was it originally developed? Was it because... a) You or one of the founders needed it for personal use?	d5b_a_personaluse
No	No	No	No	No	Yes	No	No	Thinking about the new or customized product or service, around which [NAME BUSINESS] was founded, why was it originally developed? Was it because... b) You or one of the founders needed it for use at a previous job or business?	d5b_b_previousjob
No	No	No	No	No	Yes	No	No	Thinking about the new or customized product or service, around which [NAME BUSINESS] was founded, why was it originally developed? Was it because... c) You or one of the founders thought about starting a business based on it or to sell it to someone else?	d5b_c_startingbus
No	No	No	Yes	Yes	Yes	Yes	Yes	Now, I will read you a list of customer locations. When I am done reading, please select only one answer choice for your response. During calendar year YYYY, where were most of [NAME BUSINESS]'s customers located? Would you say . . .	d8_customer_locations
No	No	No	Yes	Yes	Yes	Yes	Yes	During calendar year YYYY, were any of [NAME BUSINESS]'s sales made to individuals, businesses, or governments outside the United States?	d8a_international_sales
No	No	No	Yes	Yes	Yes	Yes	Yes	What percent of [NAME BUSINESS]'s total sales were to individuals, businesses, or governments outside of the United States? Would you say . . .	d8b_perc_international_sales

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	Yes	Yes	Yes	Yes	Yes	During calendar year YYYY, were any of [NAME BUSINESS]'s sales made to customers through the internet, such as through the business' website or an online retailer site?	d9_internet_sales
No	No	No	Yes	Yes	Yes	Yes	Yes	What percent of [NAME BUSINESS]'s total sales were sales made to customers through the internet? Would you say ...	d9a_perc_internet_sales
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, did [BUSINESS NAME] actively seek but not obtain equity from companies, government agencies, venture capitalists, angel investors, or any other individuals who are not spouses, life partners, parents, in-laws, or children of the owners?	f5a_seek_equity
No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Have you (or other owners) withdrawn money from the business for personal use in calendar year YYYY?	f6a_personal_use
No	No	No	No	Yes	No	No	No	#N/A	f6z_family_owned
No	No	No	No	No	Yes	Yes	Yes	Was collateral required to obtain any of the debt financing options that were used in calendar year YYYY? That is, were you or was [NAME BUSINESS] required to pledge as security any personal or business assets that can be taken should the business fail to repay the debt?	f12e_collateral
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... e) Business real estate?	f12f_bus_real_estate
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... b) Business equipment or vehicles?	f12f_business equip_veh
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... c) Business securities or deposits?	f12f_business_sec_dep
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... d) Patents, copyrights or trademarks?	f12f_intellectual_prop

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... a) Inventory or Accounts receivable?	f12f_inventory_acctrec
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... h) Some other type of collateral?	f12f_other
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... g) Other personal assets?	f12f_other_pers_assets
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... h) Some other type of collateral? (SPECIFY)	f12f_otherspecify
No	No	No	No	No	Yes	Yes	Yes	What collateral was required? Was it... f) Personal real estate?	f12f_pers_real_estate
No	No	No	Yes	Yes	Yes	Yes	Yes	Did [NAME BUSINESS] make any applications for new or renewed loans or lines of credit in calendar year YYYY?	f14d_new_loans
No	No	No	Yes	Yes	Yes	Yes	Yes	Were these applications always approved, sometimes approved and sometimes denied, or always denied?	f14e_approved_denied
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of business credit history?	f14f_bus_credit_hist
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of inadequate documentation provided?	f14f_inadeq_doc
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of insufficient collateral?	f14f_insuff_coll
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of the loan requested was too large?	f14f_loan_toolarge

Appendix B – Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of not being in business long enough?	f14f_new_bus
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of other reason?	f14f_other
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of other reason (specify)?	f14f_otherspecify
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of personal credit history?	f14f_pers_credit_hist
No	No	No	Yes	Yes	Yes	Yes	Yes	Consider the most recent time [NAME BUSINESS]'s credit application was denied. Officially, was the application denied because of banks putting stricter restrictions on lending?	f14g_didnotapply
No	No	No	No	Yes	Yes	Yes	Yes	During calendar year YYYY, was there any time when [NAME BUSINESS] needed credit, but did not apply because you or others associated with [NAME BUSINESS] thought the application would be denied?	f14g_didnotapply
No	No	No	No	Yes	Yes	Yes	Yes	In calendar year YYYY, did [NAME BUSINESS] have any loan guarantees from a federal government agency, such as the Small Business Administration, or any state or local government agencies?	f14h_loan_guarantees
No	No	No	No	Yes	Yes	Yes	Yes	What was the most challenging problem your business faced in calendar year YYYY? Was it . . .	f14j_most_challenging

Appendix B – Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	Yes	Yes	Yes	Yes	What was the most challenging problem your business faced in calendar year YYYY? Other specify ...	f14j_other_specify
No	No	No	No	Yes	No	No	No	#N/A	f14i_economy_effect
No	Yes	Yes	Yes	No	No	No	No	Was this an increase, a decrease, or no change in the amount of revenue for [NAME BUSINESS] in YYYY compared to YYYY?	f16b_rev_YYYY_change
No	Yes	Yes	Yes	No	No	No	No	And what was the percentage change in revenue in YYYY compared YYYY? Your best estimate is fine.	f16c_perc_change
No	Yes	Yes	Yes	No	No	No	No	Was this an increase, a decrease, or no change in total expenses for [NAME BUSINESS] in YYYY compared to YYYY?	f17b_total_exp_YYYY_change
No	Yes	Yes	Yes	No	No	No	No	And what was the percentage change in total expenses in YYYY compared to YYYY? Your best estimate is fine.	f17c_perc_change
No	No	No	Yes	Yes	Yes	Yes	Yes	Please estimate [NAME BUSINESS]'s total research and development expenses for calendar year YYYY, including materials, equipment, space, salaries, wages, benefits, and consulting fees?	f19a_res_dev_amt_YYYY
No	No	No	No	Yes	Yes	Yes	Yes	Investments in intangible assets are expenditures expected to produce long-term benefits for businesses. I'm going to read you some types of intangible assets. When thinking about each category, please consider the cost of in-house activities in these areas including the time of the business owner(s), as well as services or license fees from outside providers. Did [NAME BUSINESS] have expenditures in [ITEM/The design of new and improved products and services] in calendar year YYYY?	f19b_a_design

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	Yes	Yes	Yes	Yes	Investments in intangible assets are expenditures expected to produce long-term benefits for businesses. I'm going to read you some types of intangible assets. When thinking about each category, please consider the cost of in-house activities in these areas including the time of the business owner(s), as well as services or license fees from outside providers. Did [NAME BUSINESS] have expenditures in [ITEM/Investments in software or databases] in calendar year YYYY?	f19b_b_investments
No	No	No	No	Yes	Yes	Yes	Yes	Investments in intangible assets are expenditures expected to produce long-term benefits for businesses. I'm going to read you some types of intangible assets. When thinking about each category, please consider the cost of in-house activities in these areas including the time of the business owner(s), as well as services or license fees from outside providers. Did [NAME BUSINESS] have expenditures in [ITEM/Brand development such as advertising or marketing] in calendar year YYYY?	f19b_c_brand_dev
No	No	No	No	Yes	Yes	Yes	Yes	Investments in intangible assets are expenditures expected to produce long-term benefits for businesses. I'm going to read you some types of intangible assets. When thinking about each category, please consider the cost of in-house activities in these areas including the time of the business owner(s), as well as services or license fees from outside providers. Did [NAME BUSINESS] have expenditures in [ITEM/Organizational development such as company formation expenses or management consulting] in calendar year YYYY?	f19b_d_org_dev

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	Yes	Yes	Yes	Yes	Investments in intangible assets are expenditures expected to produce long-term benefits for businesses. I'm going to read you some types of intangible assets. When thinking about each category, please consider the cost of in-house activities in these areas including the time of the business owner(s), as well as services or license fees from outside providers. Did [NAME BUSINESS] have expenditures in [ITEM/Worker training] in calendar year YYYY?	f19b_e_worker_training
No	No	No	No	Yes	Yes	Yes	Yes	Investments in intangible assets are expenditures expected to produce long-term benefits for businesses. I'm going to read you some types of intangible assets. When thinking about each category, please consider the cost of in-house activities in these areas including the time of the business owner(s), as well as services or license fees from outside providers. Did [NAME BUSINESS] have expenditures in [ITEM/Any other intangible asset investments] in calendar year YYYY?	f19b_f_other
No	No	No	No	Yes	Yes	Yes	Yes	Investments in intangible assets are expenditures expected to produce long-term benefits for businesses. I'm going to read you some types of intangible assets. When thinking about each category, please consider the cost of in-house activities in these areas including the time of the business owner(s), as well as services or license fees from outside providers. Did [NAME BUSINESS] have expenditures in [ITEM/Any other intangible asset investments - specify] in calendar year YYYY?	f19b_f_other_specify
No	No	No	No	Yes	No	No	No	Thinking about all the intangible asset expenditures [LIST IF NECESSARY] you just told me about, please estimate [NAME BUSINESS]'s total expenses on intangible assets for calendar year YYYY.	f19c_intangassets_amt

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, how much money did (BUSINESS NAME) spend on [INTANGIBLE ASSETS ITEM]/The design of new and improved products and services?	f19c_a_design_amt
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, how much money did (BUSINESS NAME) spend on [INTANGIBLE ASSETS ITEM]/Investments in software or databases?	f19c_b_investments_amt
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, how much money did (BUSINESS NAME) spend on [INTANGIBLE ASSETS ITEM]/Brand development such as advertising or marketing?	f19c_c_brand_dev_amt
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, how much money did (BUSINESS NAME) spend on [INTANGIBLE ASSETS ITEM]/Organizational development such as company formation expenses or management consulting?	f19c_d_org_dev_amt
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, how much money did (BUSINESS NAME) spend on [INTANGIBLE ASSETS ITEM]/Worker training?	f19c_e_worker_training_amt
No	No	No	No	No	Yes	Yes	Yes	During calendar year YYYY, how much money did (BUSINESS NAME) spend on [INTANGIBLE ASSETS ITEM]/Any other intangible asset investments?	f19c_f_other_amt
No	No	No	No	Yes	Yes	Yes	Yes	Did [NAME BUSINESS] file for Chapter 11 bankruptcy protection at any time during calendar year YYYY?	f32_chap11_bankruptcy
No	No	No	No	Yes	No	No	No	Now I'd like you to think about how much you expected [NAME BUSINESS] to grow since the business was started. How much do you think [NAME BUSINESS] met your expectations for growth between when the business was started and December 31, YYYY? Would you say [NAME BUSINESS]'s growth ...	f33_expected_growth

Appendix B - Continued

The question appear in follow-up								Question	Variable Name
0	1	2	3	4	5	6	7		
No	No	No	No	Yes	No	No	No	Compared to [NAME BUSINESS]'s revenues for calendar year YYYY, what do you expect [NAME BUSINESS]'s revenues will be in calendar year 2011? Do you think revenues will . . .	f34_future_revenue
No	No	No	Yes	No	No	No	No	What was the primary field of study for this degree?	g9_fieldofstudy_resp
No	No	No	Yes	No	No	No	No	What was the primary field of study for this degree?	g9_fieldofstudy_resp_2nd
No	No	No	Yes	No	No	No	No		g9_fieldofstudy_cip_desc
No	No	No	Yes	No	No	No	No		g9_fieldofstudy2nd_cip_desc
No	No	No	No	Yes	Yes	Yes	Yes	What is your marital status?	g10b_marital_status
No	No	No	No	Yes	Yes	Yes	Yes	Including the equity in your home and business, what is your approximate total net worth, which are all your assets minus all debts?	g10c_net_worth
No	No	No	No	Yes	No	No	No	How much do you agree with the following statement? In uncertain times, I usually expect the best. Would you say you . . .	g10d_personal_outlook