ESSAYS ON THE RISK AND VARIABILITY OF FARM HOUSEHOLD CONSUMPTION

by

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Dedicated to my cats – all hail the catriarchy.

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ABSTRACT

This dissertation consists of three essays that attempt to fill a gap in the agricultural economics literature. Most academic research on the topic of agricultural finance focuses on the farm business and ignores the household itself. This dissertation is an acknowledgement that the men and women who raise livestock and cultivate crops do not participate in their profession to maximize some abstract measure of risk adjusted rate of return, but ultimately to earn a living and provide for their household. By examining consumption, the dollars spent on goods and services, food and shelter, and all other non-business-related expenses that define someone's lifestyle, this dissertation attempts to directly study the well-being of U.S. farm households. The first essay quantifies the dollar-for-dollar effect of fluctuations in incomes on consumption, with a specific emphasis on the tariff relief payments of the U.S. – China trade war. The second essay offers an in-depth study on the variability of farm household consumption and aims to put the magnitude of that variability into context. The third essay measures the riskiness of the farm household's income sources from the perspective of their consumption, and analyzes characteristics associated with higher or lower levels of risk.

CHAPTER 1. FARM HOUSEHOLDS' CONSUMPTION OF TARIFF RELIEF PAYMENTS

1.1 Abstract

This essay examines the consumption behaviors of a nationally representative sample of households who own and operate a family farm by estimating the marginal rate at which they consumed various income sources over the 2008-2019 period. Compared to earlier studies, farm household consumption spending is more resilient to fluctuations in incomes and exhibits greater persistence. Tariff relief payments received in 2018 were consumed at a significant rate which helped dampen a sizable decrease in consumption associated with the U.S. - China trade war. Consumption behaviors are contrasted across commercial, intermediate, and residence farms, as well as the farm debt to asset ratio.

1.2 Introduction

Farm income has increased every year from 2016 to 2020. This time period includes the U.S. - China trade war that targeted exports of America's agricultural commodities and the COVID-19 pandemic that significantly hampered the global real economy. This increase in incomes was made possible due to significant increases in ad hoc government payments to farmers. In 2016, government payments totaled nearly $13 billion. In 2020, government payments totaled over $46 billion, a 258 percent increase over a four-year period (USDA ERS 2021). The first of these ad hoc programs was the 2018 Market Facilitation Program (MFP1). At the time it was authorized, the program was the single largest U.S. farm subsidy program in history. Payments from the 2019 Market Facilitation Program (MFP2) totaled over $14 billion – nearly double that of any other farm support program in the preceding quarter-century.

The Market Facilitation Program was implemented to "provide assistance to farmers and ranchers with commodities directly impacted by unjustified foreign retaliatory tariffs" (USDA FSA 2018). While tariffs affected hundreds of billions of dollars of commodities, soybean producers experienced one of the largest shares of lost market revenue and best exemplify the negative effects of the trade war. For a number of years, the U.S. had been the global leader in soybean production, with exports to China totaling up to nearly ten times more than that of the second-place destination (US Census Bureau 2020). In 2016, U.S. soybean exports to China totaled over $14.2 billion, but by 2018, they had decreased to under $3.2 billion (US Census Bureau 2020; USDA FSA 2020). In 2020, Brazil surpassed the U.S. in soybean production, highlighting the impacts of the trade war on global supply chains and concerns of how long-lived those changes may be.

It is impossible to know what would have happened to the farm economy if the U.S. - China trade war had not occurred, and so the degree to which MFP1 and MFP2 compensated farmers for decreases in farm incomes from non-government sources will never be known with certainty. However, there is evidence that MFP1 and MFP2 may have over-compensated certain types of farms, at least in the short run, while under-compensating others (Janzen and Hendricks 2020). This article takes a different approach. Instead of focusing on farm incomes, this article examines the impact of the tariff relief payments on farm household well-being, as captured by household consumption spending. Examining consumption spending, rather than incomes, is preferred because farm households exhibit consumption smoothing (Girao, Tomek, and Mount 1974; MacMillan and Loyns 1969; Mullen, Powel, and Reece 1980). With consumption smoothing, a change in income may not lead to a change in household well-being. As a result, an examination of incomes alone may not accurately capture changes in well-being.

Understanding how farm households allocate different income sources is a crucial component of policy design. If household consumption spending is sensitive to changes in income then stimulus payments can spur aggregate consumption and additional economic growth. Further, if households spend anticipated income shocks, then economic stimulus can be achieved more quickly simply by announcing them in advance. This research finds evidence for both. We examine the consumption behaviors of a nationally representative sample of farm households who own and operate a farm by estimating their marginal propensity to consume (MPC) multiple income sources, including off-farm incomes, Market Facilitation Program payments, other government payments, and net farm incomes (all farm-related income excluding government sources). While prior research has primarily focused on examining the commercial farms which are responsible for the majority of agricultural production, we also estimate the MPC's of intermediate and residence farms. In doing so, we can highlight how the consumption of different income sources changes as households become increasingly focused on their farm operation and less dependent on non-farm work to generate income. Further, our examination of residence farms may be generalizable to similar households who own and operate a small non-farm business.

Despite the increasing government payments and incomes, farm bankruptcies and agricultural loan delinquency rates have also been increasing since 2014 (Federal Reserve Bank of St. Louis 2020; Newton and Sesenich 2020). Previous research suggests that small farms are consistently more likely to fail than large farms, leading to industry consolidation, which in turn leads to increases in the market power of those that remain (Sexton 2013; MacDonald, Hoppe, and Newton 2018). Because of the importance of industry consolidation and market power, it is informative to examine the impacts of government programs across the farm size spectrum. We identify significant differences in the consumption behaviors of households who operate commercial, intermediate, and residence farms, which is consistent with the recent literature identifying heterogeneity in the marginal propensity to consume (Lewis, Melcangi, Pilossoph 2019).

The typical farm households' balance sheet contains a considerable amount of equity outside of the family home, differentiating it from that of a typical non-farm household where the largest source of equity is the family home. The adjacent literature on household finance suggests that wealthy households' consumption spending responds sharply to unexpected income shocks (Kaplan, Violante, and Weidner 2014; Kaplan and Violante 2014; Ganong et al. 2020). These so-called "wealthy hand-to-mouth" households seemingly defy the life-cycle consumption hypothesis, and their large consumption response is often attributed to the composition of their wealth. Specifically, households are less able to mobilize illiquid forms of wealth to smooth their consumption spending. This recent development in the literature has yet to be addressed within the context of the farm household. To help fill this gap in the literature and explore how the consumption behavior of farm household changes with the composition of their wealth, we show how the marginal propensity to consume various income sources change across the farm's debt to asset ratio.

This research makes four key contributions to the literature. First, we show that changes in net farm income (all farm-related income excluding government sources) and off-farm income are associated with smaller changes in consumption spending than suggested by previous studies. Prior studies have consistently found that commercial farms consume net farm incomes at a marginal rate of one to three percent and off-farm incomes at a marginal rate of five to ten percent

(Langemeier and Patrick 1990; Carriker et al. 1993; Whitaker 2009). By contrast, we estimate these rates to be less than one percent and less than four percent respectively. This implies that over the 2008-2019 study period, the households of commercial farms have had their consumption spending become more stable, less sensitive to changes in incomes, and have been better able to smooth their consumption compared to earlier time periods. Second, we show that dollar-for-dollar MFP payments received in 2018 had a significantly larger impact on consumption than any other income source, and household spending would have been significantly lower without these payments. The large positive impact in 2018 may partly be due to the pre-spending of the anticipated second tranche of MFP1 which was largely disbursed in early 2019. Third, we find a statistically significant and economically large difference in the rate at which MFP payments were consumed by households operating commercial farms, intermediate farms, and residence farms. Dollar-for-dollar, 2018 MFP payments going to residence farms are associated with an increase in household consumption spending over five times that of payments going to intermediate farms, and over six times that of payments going to commercial farms. We estimate that households operating residence farms consumed 168 cents per dollar of tariff relief received in 2018, while households operating intermediate farms consumed 38 cents per dollar, and those operating commercial farms consumed 27 cents per dollar. Finally, our analysis suggests that farm solvency has a significant impact on how income shocks affect the consumption spending of the farm household, and that those impacts vary depending on both the income source and farm typology. Regardless of farm typology, higher debt to asset ratios are associated with less persistent consumption spending. This finding highlights the importance of capturing the composition of household wealth and helps explain a possible source of heterogeneity in the consumption of MFP payments.

These contributions are important and timely for several reasons. First, economic stimulus and relief packages are likely to be used in the future. Secondly, the findings further our understanding of the well-being of farm households and how they were affected by a global trade war, volatile incomes, and changing structures of farm support programs.

In the following sections we first explore the data used in this article and highlight certain peculiarities which make it necessary to use a specific econometric approach, then we illustrate the empirical methodology in detail, followed by a discussion of the results. The final section concludes with a discussion of the broader implications of our key empirical findings.

1.3 Data

This article utilizes data from the USDA's Agricultural Resource Management Survey (ARMS) covering 2008 to 2019 (USDA FSA and USDA ERS 2019). Each year, a stratified sample of farms across the contiguous United States is selected by the USDA's Economic Research Service, and the USDA's National Agricultural Statistics Service (NASS) constructs weights such that the sample is representative of the national farm economy.

The surveys are completed by the primary operator of each farm, so data from the household section and the farm income sections of the survey may correspond to different individuals. In order to be certain that consumption spending and farm incomes correspond to the same household, we examine only family farms that are partnerships or sole proprietors as well as owned and operated by the same household. The omitted farm entities represent roughly one-quarter of all agricultural production and one-tenth of farm households. The USDA ERS defines farms which have either exceptionally low gross farm incomes or total household incomes which fall below the poverty line as "limited resource" farms. These limited resource farms are also omitted from this sample. We also omit from the analysis any household reporting less than $5,000 or more than $400,000 in real 2018 consumption, altering these cutoffs do not result in any meaningful changes to the results.

Because ARMS is repeated cross-section, sequentially repeated observations of the same farm are uncommon, and thus typical panel data techniques cannot be used. However, pseudo-panel techniques may be used with ARMS to obtain asymptotically consistent estimates (Whitaker 2009). Pseudo-panels are constructed by categorizing observations into like groups, called cohorts, such that the cohort's characteristics are unlikely to change over time, and then using the mean value of the cohort as a single observation (Verbeek and Nijman, 1992). In this article, we use commodity specializations and state to group farm households with similar production practices together into cohorts.

The commodity specialization groupings are barley, oats, and wheat; corn, soybeans, and sorghum; miscellaneous crops (cotton, tobacco, and general crop farms); fruits and nuts; vegetables and nursery; beef cattle; poultry; hogs and other livestock; dairy. A farm is assigned to one of these commodity specializations based on the commodity which composes more than half of their total value of production. We construct three pseudo-panels using these commodity groupings and state, one pseudo-panel containing only commercial farms, another containing only intermediate farms, and a third pseudo-panel containing only residence farms. We use the Economic Research Service's current definition of commercial, intermediate, and residence farms. A commercial farm is any farm with greater than $350,000 in gross cash farm income regardless of the operator's primary occupation. An intermediate farm is a farm with less than $350,000 in gross cash farm income and the operator's primary occupation is farming. A residence farm is a farm with less than $350,000 in gross cash farm income and the operator's primary occupation is either not-farming, or if the operator's primary occupation is farming, they are also retired from farming. While the Economic Research Service uses nominal dollars to define farm class, we use real 2018 dollars. A cohort observation is only constructed if it consists of at least ten farms in a given year, the reasoning for this is explained in more detail in the next section. If a cohort is not observed in three consecutive years those non-consecutive observations are omitted from construction, this is also explained in the next section.

Consumption spending is not measured continuously by ARMS. The phase III survey of ARMS measures various consumption categories with discrete responses associated to specified value ranges. The consumption variable used in this analysis is constructed by converting each discrete response to the mid-point of the respective range and then summing across all consumption categories. The 34 possible discrete responses of 11 expenditure categories result in several million possible values of the consumption variable. Of the individual farm observations of consumption used in the analysis, over 23 percent have a distinct value, and over 51 percent of the observations take a value seen six or fewer times. Despite being constructed from discrete responses, the consumption variable has a very large amount of variability. Consumption spending levels are generally highest for commercial farms, followed by residence farms, and then intermediate farms.

We allocate income from government sources to the household by multiplying the farms reported income from that source by the percentage of the farm business income received by the household. For a sole proprietor that percentage is 100, for a partnership with equal owners that percentage would be 50, and so on. We define net farm income as the household's farm-related income minus government payments (MFP and other).

Commercial farm household income is mostly composed of farm related sources, but also contains a relatively high level of non-farm income. Residence farm household's income is almost entirely composed of their high off-farm incomes, and net farm income is often negative.

Intermediate farm households have off-farm income which is considerably less than that of residence farm households, farm related incomes which are considerably less than commercial farm households, and generally have lower total incomes than both groups. Regardless of farm size, off-farm income is an important part of total household income. Off-farm income may be changed year to year as a risk management strategy and has been increasing as a proportion of total household income (Mishra and Sandretto 2002; Mishra et al. 2010; Jodlowski 2020).

In order to effectively smooth their consumption spending in low-income years the farm household must be able to draw upon savings or tap into credit against those savings. The typical household net worth has been increasing steadily in real terms, more-so for commercial farm households. While intermediate farm households have lower incomes than residence farms, they generally have a higher net worth. Commercial farm households are far and away the wealthiest group. Most of this growth in household net worth occurs over the exceptionally high farm income years of 2010-2014, which coincides with widespread droughts across the U.S. and North America. While the typical farm household has a relatively high net worth compared to nonfarm households, that wealth is largely illiquid. Tapping into lines of credit may be an easier way to generate cash flow than selling off farm assets, but access to credit can quickly become difficult if the farm is exceptionally leveraged. There was a downward trend in farm debt to asset ratios between 1992 and 2011 (Ifft, Patrick, and Novini 2014), but there is an upward trend from the early 2010's onward. The farm debt to asset ratio is highest on average for commercial farms, followed by intermediate farms and then residence farms.

Our discussion of the Market Facilitation Program requires an understanding of its timeline. In July of 2018 the USDA announced that it would authorize up to $12 billion in assistance to farmers impacted by the U.S. - China trade war. In August of 2018 the USDA announced the details of the Market Facilitation Program as well as other smaller programs which purchased affected commodities. In early September of 2018 the Market Facilitation Program was launched, this 2018 program is commonly referred to as MFP1 to differentiate it from the identically named programs authorized and implemented in 2019 (MFP2) and 2020 (MFP3). Farmers worked with their local Farm Service Agency (FSA) representative to sign up for the program. The program payments are based on the quantity of each covered commodity produced, with each commodity having its own payment rate. Payments from MFP1 were capped at a combined $125,000 for corn, cotton, sorghum, soybeans, and wheat, per person or legal entity, as well as a combined $125,000 for dairy and hogs. Additionally, to be eligible for the program the average adjusted gross income for tax years 2014, 2015, and 2016 must be less than $900,000. The payments from MFP1 were split into two tranches, each based on 50 percent of the farmers production. The first tranche of MFP1 was received in the fall of 2018. The second tranche of MFP1 was confirmed by Secretary of Agriculture Sonny Perdue on October 29th of 2018 and formally announced by the USDA on December 17th. Farmers who applied for the second tranche before the federal government shutdown on December 22nd received the payments in December, while farmers who did not received the payments in early 2019.

The 2019 version of the program was expanded in size and scope, covering more commodities with larger dollar amounts. On May 23rd of 2019 MFP2 was announced with guidance that up to three tranches could be made depending on market conditions. Farmers began receiving the first tranche of MFP2 as early as July 2019. On November 15th of 2019 the USDA issued the second tranche of MFP2, followed by the third tranche on February 3rd of 2020. Table 1.1 and Table 1.2 contain a breakdown of how MFP payments differed by farm type, commodity specialization, and calendar year of receipt. The proportion of individual farms receiving an MFP payment increased from 2018 to 2019 for every single commodity specialization grouping, but the probability of receiving a payment and the increase in probability from 2018 to 2019 were higher for commercial farms than intermediate or residence farms. Likewise, the average of MFP payments among farms who received a payment, and the increase in that average, are considerably higher for commercial farms than intermediate and residence farms. The expansion of the 2019 program was much more extensive for commercial farms than intermediate or residence farms, which may be important in explaining any differences in consumption of the MFP payments across farm type and year, possibly due to differences in the expectation and realization of program expansion.

1.4 Empirical Methodology

The life-cycle consumption hypothesis has been shown to model the consumption behaviors of farm households more accurately than the permanent income, relative income, and partial adjustment hypotheses (Langemeier and Patrick 1990). Carriker et al. (1990) derived a version of the life-cycle model that is appropriate when money is infungible and households consume various income sources differently. Whitaker (2009) then adapted the Carriker model for use with ARMS pseudo-panels, and the empirical specification is shown in Equation 1.1:

$$\bar{C}_{j(t),t} = \beta_0 + \sum_{s=1}^{Z}(\beta_{1s}\bar{Y}_{s,j(t),t}) + \beta_2 \ \bar{C}_{j(t-1),t-1} + \beta_3 \ \bar{W}_{j(t),t} + \epsilon_{j(t),t} \qquad (1.1)$$

where the overbar $\bar{\ }_{j(t),t}$ is the mean of cohort $j(t)$ at time t, C is household consumption spending, W is household net worth, and S indexes the income sources Y: net farm income (all farm-related income except government sources), off-farm income, Market Facilitation Program payments, and other government payments, and β_{1s} is the marginal propensity to consume the s income source.

This model has unique empirical considerations because the individual farms which comprise a given cohort changes each year. While the cohorts are created such that individual farms should be placed into the same cohort each time it is observed, due to random sampling the farms which are observed within the cohort each year are always different. The state-commodity cohort j observed in time t consists of different farms than the one observed in $t - 1$. Because the farms within cohort $j(t)$ are not observed in $t - 1$, the lagged mean consumption of $j(t)$ is never observed, therefore one must use the observed mean consumption of cohort $j(t - 1)$ in $t - 1$ as a proxy. The use of this proxy in place of the true lagged variable creates bias. The unobservable difference in the mean consumption of cohort $j(t)$ and $j(t - 1)$: $\bar{C}_{j(t-1),t-1} - \bar{C}_{j(t),t-1} = e$, is included in the error term $\epsilon_{c(t),t}$. The proxy variable is therefore correlated with the error term because it is in fact included in the error term. Dynamic-pseudo-panels with lagged variables containing this bias may be consistently estimated using instrumental variable techniques (McKenzie, 2004). Following Whitaker (2009), we use twice lagged consumption and single lags of all independent variables are used as instruments for once lagged consumption.

High sampling error of small samples can be problematic with dynamic pseudo-panels, and the speed at which OLS and IV estimates converge is dependent on both the number of time periods and the number of observations within a single cohort (McKenzie, 2004). Whitaker (2009) addresses this concern by limiting the analysis to only cohorts comprised of at least 10 individual farm observations, each of which represent hundreds or even thousands of other similar farms due to the stratified sampling nature of ARMS and the observation weights constructed by NASS. We similarly require a cohort to have at least 10 farm level observations to be included in the analysis and note that our sample is several years longer than Whitaker (2009) and should therefore have more preferable asymptotic properties.

It is evident from the literature that consumption decisions are affected by the financial state of the household. While the life-cycle consumption hypothesis incorporates household wealth, it does not include information on the composition of that wealth. In order to examine how the composition of wealth affects consumption behavior the empirical models are also estimated with the addition of interaction terms. We estimate MPC's across the debt to asset ratio by including interactions on each dependent variable, as shown in Equation 1.2:

$$\bar{C}_{j(t),t} = \beta_0 + \sum_{s=1}^{Z} (\beta_{1s}\bar{Y}_{s,j(t),t}) + \beta_2\ \bar{C}_{j(t-1),t-1} + \beta_3\ \bar{W}_{j(t),t} + \sum_{s=1}^{Z} (\beta_{4s}\bar{Y}_{s,j(t),t}\overline{DA}_{j(t),t}) + \beta_5\ \bar{C}_{j(t-1),t-1}\overline{DA}_{j(t),t} + \beta_6\ \bar{W}_{j(t),t}\overline{DA}_{j(t),t} + \epsilon_{j(t),t}. \tag{1.2}$$

Equation 1.1 and Equation 1.2 are estimated using the three pseudo-panels – commercial farms, intermediate farms, and residence farms - with annual fixed effects and observation weights created by NASS. In the IV estimation twice lagged consumption and single lags of all other independent variables are used as instruments for once lagged consumption. Standard errors are estimated with a jackknife procedure using replicate weights constructed by NASS.

1.5 Results and Discussion

Table 1.3 contains the regression results for the primary model. As mentioned in the prior sections the OLS models are biased and so all future references to the MPC's are referring to the results of the IV models. Net farm income (all farm related income excluding government sources) is statistically significant to the 99 percent confidence level for all farm typologies. Commercial farms have an MPC of 0.26 percent, implying that an increase (decrease) in net farm income of $100 is associated with an increase (decrease) in consumption of 26 cents. Intermediate farms have an MPC of 3.2 percent, and residence farms have an MPC of negative 0.54 percent. Off-farm income is statistically significant to the 99 percent confidence level for all farm typologies. The MPC of off-farm income is 1.1 percent for commercial farms, 3.5 percent for intermediate farms, and 2.8 percent for residence farms. These results imply that changes in net farm income are associated with considerably smaller changes in consumption spending than an equivalent change in off-farm income. The results for commercial farms are notably smaller than those of previous studies which consistently estimate an MPC of between one and two percent for net farm incomes and five to ten percent for off-farm incomes (Langemeier and Patrick 1990; Carriker et al. 1993; Whitaker 2009). A likely explanation for this difference from the literature might be that the strong balance sheets resulting from the high farm income years of 2010-2014 better enabled the farm household to smooth their consumption compared to years covered in prior studies.

No prior studies have estimated the MPC's of net farm income and off-farm income separately for intermediate and residence farms. Our results highlight how the relative importance of farm and off-farm incomes change as the household becomes more focused and dependent on the farm enterprise. A household operating a residence farm is largely unaffected by changes in their farm incomes as it is a very minor part of their total household income – and is most often negative. For those operating intermediate farms a decrease in farm incomes is associated with a decrease in consumption spending but expanding the size of the operation to that of a commercial farm causes the consumption response to fall dramatically. The MPC of off-farm income is larger than that of net farm income for all three farm classifications, and highlights the importance of off-farm work as a risk management tool even as the household focuses the majority of their efforts on the farm.

The MPC of Market Facilitation Program payments differs significantly depending on whether the household operates a commercial, intermediate, or residence farm. Market Facilitation Program payments were consumed at a marginal rate of 3.5 percent by household's operating commercial farms, statistically significant to the 90 percent confidence level. Household's operating intermediate farms did not consume the MFP payments at a statistically significant rate. Household's operating residence farms however, consumed the MFP payments at an economically large 52 percent rate, statistically significant to the 99 percent confidence level. We believe that these results are not reflective of the true consumption response to the MFP payments. Treating the MFP payments received in 2018 and those received in 2019 as distinct income sources reveals significant heterogeneity in their consumption, which this model specification averages into incorrect coefficients of little statistical significance.

Table 1.4 reports the results of splitting the MFP payments into two variables by the year in which they were received. None of the coefficients except for those on the MFP payments themselves change meaningfully from the base model. Household's operating commercial farms consumed MFP payments in 2018 at a marginal rate of 21 cents on the dollar, statistically significant to the 99 percent confidence level, but did not consume payments received in 2019 at a statistically significant rate. Household's operating intermediate farms consumed the MFP payments received in 2018 at a marginal rate of 28 cents on the dollar, but decreased their consumption by 18 cents for every dollar received in 2019, both of these results being statistically significant to the 99 percent confidence level. Household's operating residence farms consumed MFP payments received in 2018 at a rate of 134 cents on the dollar, significant to the 99 percent confidence level, but did not consume payments received in 2019 at a statistically significant rate. Regardless of farm classification examined, the MPC's of MFP payments received in 2018 are economically large and highly statistically significant, but the MPC's of the MFP payments received in 2019 are either negative or near-zero.

We hypothesize that the disparate consumption of MFP payments received in 2018 and 2019 is due to anticipatory spending. Because recipients of the first tranche of MFP1 were aware that they had a second payment coming in late 2018 or early 2019 based on the remaining 50 percent of their value of production, they may have spent that first tranche more aggressively. Farm households may have effectively "pre-spent" their second tranche of MFP1, possibly including moving some of their planned consumption spending from early 2019 into late 2018. This explanation of anticipatory spending is made plausible by the second tranche of MFP1 being split across the calendar years. If the MFP1 payment received in 2019 were already consumed in 2018 it would be manifested in the data as a higher MPC for the payments received in 2018 and a smaller MPC in 2019 (and an increasingly negative MPC in 2019 if planned expenditures for 2019 were moved to 2018), which would fit our empirical findings.

There exists evidence in the literature that supports this theory of pre-spending an anticipated income shock. One such study found that Alaskan households did not change their consumption significantly in the quarter in which they received the Permanent Fund Dividend (PFD) but did increase their consumption when receiving a tax refund (Hseih 2003). The PFD is received annually by every Alaskan resident and is announced at least six months prior; income tax refunds however are far less predictable in their size and timing. Hseih (2003) concludes that households will effectively smooth income changes when those changes are relatively small, predictable, or when the cost of mental processing is low, and income changes will not be smoothed when those changes are large, unpredictable, or when the cost of mental processing is high. Our hypothesis for the anticipatory spending of the second tranche of MFP1 is consistent with Hsieh (2003). If true, this hypothesis would also indicate that the farm household's ability to smooth their consumption of income shocks is dependent on their knowledge of and ability to accurately predict future incomes. As equity in the farm enterprise is not exceptionally liquid, there is likely a delay in the farmers ability to convert equity into cash flow. By further examining the degree to which anticipatory spending occurs as the time between the announcement and realization of the income shock varies, one could identify the timespan over which farm households are wealthy hand-to-mouth.

While the body of literature surrounding anticipatory spending offers a plausible explanation for the disparity in the MPC of MFP payments depending on which year they were received, there are other possible confounding factors. If farmers expected a quick resolution to the trade war – say because they thought trade wars are good and easy to win, as tweeted by President Donald Trump in 2018 – then they may have seen MFP1 as a one-time windfall. In such a case, farmers may have interpreted MFP2 as a negative signal about the likelihood of a continued trade war and the future health of the farm economy, causing them to save more and consume less than those who did not receive such a signal. Similarly, if households of intermediate or residence farms expected MFP2 to be expanded in scale and scope, but the majority that expansion was received by commercial farms, then they may have interpreted the less than expected payment from MFP2 as a negative signal.

While the second tranche of MFP1 could have been received either prior to the government shutdown on December 22nd of 2018 or after the shutdown ended on January 25th of 2019, there is the question of whether there was enough time to consume a payment received in 2018 within that same calendar year. One possible solution to this question is to aggregate the 2018 and 2019 data and treat it as a single year.

Table 1.5 reports the results of combining the 2018 and 2019 data and treating it as a single year before construction of the pseudo-panel cohorts. The MPC of MFP payments over the aggregated 2018 and 2019 period was 6.6 percent for household's operating commercial farms, 18 percent for household's operating intermediate farms, and 62 percent for household's operating residence farms. Except for the MFP payments and the 2018 fixed effect (which is now an average of the 2018 and 2019 fixed effect) the coefficients of the other variables are not meaningfully changed from those of the prior two models. The economically large and statistically significant negative fixed effects in 2018 (compared to the 2016 base year) is likely attributable to the U.S. -

China trade war, but we do not assert causality. However, other studies using difference-in-difference techniques show that counties which were more directly affected by tariffs experienced a significant decrease in consumption compared to those counties less affected by tariffs (Waugh 2019). Using the mean non-zero MFP payment received in 2018 reported in Table 1.2 and MPC's reported in Table 1.4**,** we calculate the estimated consumption effect of the MFP payments received in 2018 and compare it to the 2018 fixed effect. For household's operating a commercial farm which specialize in corn, soybeans, or sorghum, the estimated consumption effect is $9,657, which is $571 less than the 2018 fixed effect of negative $10,228. For household's operating an intermediate farm which specializes in corn, soybeans, or sorghum, the estimated consumption effect is $2,968, which is $3,345 less than the 2018 fixed effect of negative $6,314. For household's operating a residence farm which specializes in corn, soybeans, or sorghum, the estimated consumption effect is $9,817, which is $5,976 higher than the 2018 fixed effect of negative $3,841. Using either of the smaller MPC's for residence farms from the other two models yields similar results. The consumption effects of the trade war are not limited to the 2018 fixed effect, the decrease in farm income from non-government sources is also associated with a decrease in consumption. The MPC of farm income is so small that even attributing the entire difference in farm income from non-government sources from 2016 to 2018 to the trade war does not yield an estimated decrease in consumption large enough to alter the discussion from what is offered above.

While in aggregate the MFP payments did not offset the decrease in consumption which is likely attributable to the U.S. - China trade war, the MFP payments received in 2018 largely dampened any decreases in consumption experienced by farms benefiting from the program, and farms of certain typologies may have been made more than whole and experienced an increase in their consumption spending.

For all three variations of the model discussed so far, the coefficients for lagged consumption are significantly higher than those estimated in previous studies using older data from the same source (Whitaker 2009). A higher coefficient on lagged consumption combined with lower MPC's of both net farm income and off-farm income imply that farm household consumption expenditures are less sensitive to changes in incomes over 2008-2019 than in earlier study periods.

Table 1.6 reports the results of the interaction model using the separated MFP payments. Generally, the interaction models reveal that higher debt to asset ratios are associated with a smaller coefficient on lagged consumption and higher MPC's, the only significant exceptions being residence farms' MPC's of MFP payments and other government payments. These results imply that as the farm's debt to asset ratio farm increases the household smooths their consumption spending less effectively when faced with changes in incomes. An increasing MPC and decreasing coefficient on lagged consumption makes intuitive sense. As the farm business becomes increasingly leveraged and financially strained it becomes harder for the household to use the farms assets to generate cash flow to smooth their consumption spending. For intermediate and commercial farms, the MPC of MFP payments is increasing with the debt to asset ratio, which may imply that more financially strained farms consumed the MFP payments to maintain their standard of living through the decrease in other farm incomes because they were less able to smooth their consumption with usual means compared to less financially strained farms. For residence farms however, the MPC of MFP payments is decreasing as the debt to asset ratio increases, which may imply that as leverage increases more of these payments were either saved or used to pay down debts because their household income outside of the MFP was not nearly as affected by the U.S. - China trade war.

1.6 Conclusions

The last several years has seen farm incomes comprised of more government payments than ever before. The first of these large programs was the Market Facilitation Program, intended to compensate farmers and ranchers for the damages inflicted by the retaliatory tariffs imposed on agricultural commodities during the U.S. - China trade war. The increasing size, scope, and cost of farm support programs underscores the importance of understanding their effectiveness. While other studies have examined the financial impacts of the Market Facilitation Program, we take a different approach to ascertain a more holistic view of how the farm household's well-being was affected by the MFP and other changes in income. In this article we examine the consumption behaviors of farm households and estimate their marginal propensity to consume Market Facilitation Program payments.

The farm household's marginal propensity to consume farm income (excluding government sources) and off-farm incomes over 2008-2019 are found to be notably lower than those of earlier studies. Household's operating commercial, intermediate, and residence farms have significant differences in their marginal propensity to consume, and those differences highlight their varying ability to smooth their consumption as well as their relative importance of farm and off-farm income. The effect of lagged consumption on current consumption is shown to be more persistent than in earlier studies. Together these results imply that farm household consumption spending has become more stable and resilient in the face of changes in incomes.

Farm households appear to smooth their consumption spending less effectively as their debt to asset ratio increases. Additionally, households operating residence farms with high levels of leverage consumed the tariff relief payments at a lower marginal rate than those with lower levels of leverage, implying that they instead increasingly saved or used those payments to pay down debts.

Heterogeneity in farm household consumption behaviors is found to exist across commercial, intermediate, and residence farms. Households of commercial farms' consumption spending is more persistent and less responsive to changes in incomes, implying that these households are better able to smooth their consumption spending than those that operate intermediate or residence farms. We estimate that tariff relief payments disbursed in 2018 were consumed at a rate of 21 cents on the dollar by households of commercial farms, 28 cents on the dollar by households of intermediate farms, and 134 cents on the dollar by households of residence farms.

While in aggregate the MFP payments received in 2018 did not offset the decrease in consumption associated with the 2018 fixed effect and the U.S. - China trade war, households of certain farm typologies may have been made more than whole in terms of their consumption spending. The estimated consumption effect of MFP payments received in 2018 are particularly large for residence farms specializing in corn, soybean, or sorghum, with the increase in consumption outsizing the negative 2018 fixed effect.

The tariff relief payments disbursed in 2019 appear to have been consumed much differently than those of 2018. We find evidence that some households who received payments in 2019 decreased their consumption compared to those who received nothing, all else equal. Though we also offer alternative explanations, we posit that the disparate consumption of MFP payments across years is due to anticipatory spending. Households which received the first MFP payment in 2018 would have been aware that they had a similarly sized second payment coming in early 2019.

Knowing that second payment was coming, household's may have increased their consumption spending more in 2018 with the intent of paying for that additional spending in early 2019, as well as possibly moving planned expenditures from early 2019 into 2018.

While the empirical evidence in this article fits explanations of anticipatory spending found in the literature, the existence of anticipatory spending cannot be definitively proven with only the data used in this article. The MFP offers a very attractive opportunity to examine the degree to which farm households exhibit anticipatory spending, as well as over what time frame they are wealthy hand-to-mouth. Anticipatory spending of farm households could be empirically tested using microdata which is more granular in the time dimension and examining consumption expenditures in the time period before and after the announcement and disbursal of various MFP tranches.

If the disparate consumption of tariff relief payments received in 2018 and 2019 were in fact due to anticipatory spending it would have important policy implications which are particularly relevant to the current coronavirus pandemic and future economic crises. If the spending of an anticipated increase in income begins before the receipt of that income, then the speed at which policymakers could stimulate aggregate consumption and economic stimulus can be accelerated with the trusted announcement of predictable future payments of a known amount.

Table 1.1: Proportion of Households Receiving a Market Facilitation Program Payment

	Commercial		Intermediate		Residence	
	2018	2019	2018	2019	2018	2019
barley, oats, wheat	0.44	0.81	0.37	0.68	0.28	0.51
	(0.045)	(0.021)	(0.044)	(0.049)	(0.086)	(0.074)
corn, soybeans, sorghum	0.53	0.81	0.41	0.59	0.34	0.58
	(0.021)	(0.022)	(0.027)	(0.039)	(0.030)	(0.046)
miscellaneous crops	0.25	0.61	0.02	0.06	0.00	0.02
	(0.067)	(0.053)	(0.004)	(0.010)	(0.001)	(0.005)
fruits and nuts	0.02	0.19	0.00	0.07	0.00	0.03
	(0.006)	(0.032)	(0.001)	(0.029)	(0.001)	(0.010)
vegetables and nursery	0.01	0.19	0	0.06	0	0.01
	(0.014)	(0.097)	(0)	(0.051)	(0)	(0.005)
beef cattle	0.42	0.55	0.01	0.03	0.00	0.00
	(0.082)	(0.076)	(0.005)	(0.010)	(0.001)	(0.001)
hogs and other livestock	0.20	0.39	0.01	0.03	0.00	0.02
	(0.046)	(0.068)	(0.004)	(0.006)	(0.002)	(0.004)
poultry	0.03	0.15	0.01	0.02	0	0.03
	(0.021)	(0.047)	(0.006)	(0.006)	(0)	(0.028)
dairy	0.36	0.58	0.19	0.24	0.10	0.14
	(0.037)	(0.046)	(0.053)	(0.060)	(0.120)	(0.150)

Note: Parentheses indicate standard errors

Table 1.2: Mean Non-Zero Market Facilitation Program Payments Recieved by Households

	Commercial		Intermediate		Residence	
	2018	2019	2018	2019	2018	2019
barley, oats, wheat	34,611 (3,417)	57,815 (4,867)	8,625 (1,077)	16,682 (1,152)	5,722 (1,034)	7,358 (1,843)
corn, soybeans, sorghum	45,985 (1,606)	62,780 (3,341)	10,602 (1,108)	12,769 (707)	7,326 (854)	7,358 (726)
miscellaneous crops	30,447 (8,271)	80,983 (8,746)	5,356 (2,761)	7,939 (887)	- -	3,957 (1,278)
fruits and nuts	40,914 (10,451)	61,668 (11,641)	- -	5,395 (3,726)	- -	7,107 (1,749)
vegetables and nursery	- -	111,633 (67,415)	- -	- -	- -	- -
beef cattle	30,161 (5,585)	51,836 (9,822)	9,977 (5,076)	8,343 (3,746)	- -	- -
hogs and other livestock	13,048 (2,742)	29,921 (5,014)	3,770 (722)	5,832 (752)	2,754 (512)	3,209 (785)
poultry	- -	12,613 (2,267)	- -	6,482 (3,592)	- -	- -
dairy	11,326 (1,627)	19,988 (2,638)	1,600 (416)	4,736 (868)	- -	- -

Note: Parentheses indicate standard errors. Values are omitted in the case of there being fewer than ten observations reporting a non-zero MFP payment and are indicated by a hyphen (-)

Table 1.3: Marginal Propensity to Consume

	Commercial		Intermediate		Residence	
	IV	OLS	IV	OLS	IV	OLS
Lag Consumption	0.58*** (0.027)	0.29*** (0.0085)	0.32*** (0.032)	0.19*** (0.011)	0.36*** (0.024)	0.22*** (0.0079)
Net farm income	0.0026*** (0.00042)	0.0040*** (0.00037)	0.032*** (0.004)	0.027*** (0.0032)	-0.0054*** (0.0013)	-0.0015 (0.0019)
Off-farm income	0.011*** (0.0021)	0.0099*** (0.0024)	0.035*** (0.002)	0.037*** (0.0019)	0.028*** (0.0027)	0.035*** (0.0027)
MFP payments	0.035* (0.018)	0.066*** (0.017)	-0.073 (0.053)	0.034 (0.048)	0.52*** (0.11)	0.54*** (0.092)
Other government payments	0.089*** (0.0064)	0.095*** (0.006)	0.19*** (0.023)	0.14*** (0.019)	0.061** (0.027)	0.13*** (0.026)
Household net worth	0.00067*** (0.000087)	0.00099*** (0.0001)	0.0021*** (0.00017)	0.0026*** (0.00015)	0.0042*** (0.00026)	0.0045*** (0.00024)
Year is 2009	- -	-1903.3*** (378.4)	- -	-1586.3*** (348.5)	- -	1496.4*** (221.8)
Year is 2010	-519.4 (414.5)	-2097.2*** (406.5)	40.2 (313.6)	-398.8 (330.1)	1658.8*** (163.8)	1577.6*** (164.3)
Year is 2011	752.3* (400.9)	-720.7* (366.2)	235.6 (345.8)	159 (357.3)	700.6*** (204.6)	735.6*** (211)
Year is 2012	4982.7*** (361.2)	3366.3*** (323.7)	1754.0*** (301.3)	1565.5*** (301.4)	3580.5*** (238.6)	3401.1*** (246)
Year is 2013	11326.4*** (505.5)	11391.3*** (492.7)	7118.8*** (337.6)	7135.3*** (329.4)	9928.1*** (278.3)	10407.2*** (277.9)
Year is 2014	-1395.7*** (487.8)	1594.0*** (356.5)	1827.2*** (395.7)	2514.0*** (316.1)	3694.4*** (270.5)	4903.3*** (208.4)
Year is 2015	-980.4** (430.6)	-49.8 (465.2)	-1791.4*** (528.4)	-1116.8** (498.4)	-1443.7*** (242.3)	-502.1** (234.9)
Year is 2017	1170.0*** (325.9)	778.5** (320.6)	3000.8*** (267.3)	2846.8*** (273.3)	1297.9*** (202.2)	1558.1*** (238.3)
Year is 2018	-7252.8*** (392.3)	-7959.4*** (310.2)	-6030.5*** (334.9)	-5473.5*** (291.4)	-3619.0*** (265.4)	-3523.4*** (271.3)
Year is 2019	1104.6 (926.8)	-2562.7*** (752.9)	447.5 (318.3)	-566.5* (304.1)	3088.6*** (257.6)	2587.6*** (229.7)
Constant	16894.9*** (1558.3)	31617.7*** (696.2)	20941.7*** (1118.5)	25422.2*** (497.3)	20578.1*** (826.3)	25631.2*** (378.6)
Observations	748	863	952	1092	844	985
R-squared	0.36	0.41	0.33	0.34	0.44	0.44

Note: Parentheses indicate standard errors. Twice-lagged consumption and lagged independent variables are employed as instruments. Single asterisk (∗), double asterisks (∗∗), and triple asterisks (∗∗∗) represent statistical significance at the 10%, 5%, and 1% levels, respectively

Table 1.4: Marginal Propensity to Consume – MFP Split by Year

	Commercial		Intermediate		Residence	
	IV	OLS	IV	OLS	IV	OLS
Lag Consumption	0.57*** (0.026)	0.29*** (0.0083)	0.32*** (0.032)	0.20*** (0.011)	0.35*** (0.024)	0.22*** (0.0079)
Net farm income	0.0025*** (0.00043)	0.0038*** (0.00037)	0.032*** (0.004)	0.028*** (0.0032)	-0.0029** (0.0014)	0.00067 (0.0018)
Off-farm income	0.012*** (0.0021)	0.010*** (0.0024)	0.035*** (0.002)	0.037*** (0.0019)	0.028*** (0.0027)	0.035*** (0.0026)
MFP in 2018	0.21*** (0.017)	0.24*** (0.017)	0.28*** (0.049)	0.42*** (0.067)	1.34*** (0.075)	1.34*** (0.077)
MFP in 2019	-0.0011 (0.018)	0.027 (0.017)	-0.18*** (0.063)	-0.088 (0.06)	0.056 (0.14)	0.092 (0.12)
Other government payments	0.089*** (0.0064)	0.095*** (0.006)	0.19*** (0.023)	0.14*** (0.019)	0.058** (0.027)	0.13*** (0.026)
Household net worth	0.00069*** (0.000088)	0.0010*** (0.00011)	0.0021*** (0.00016)	0.0026*** (0.00015)	0.0042*** (0.00026)	0.0044*** (0.00023)
Year is 2009	- -	-1886.8*** (375.6)	- -	-1578.6*** (348.3)	- -	1502.6*** (222.4)
Year is 2010	-533.2 (411.4)	-2080.0*** (404)	9.6 (311.8)	-396.5 (329.5)	1656.1*** (163.8)	1574.7*** (164.3)
Year is 2011	733.7* (398.5)	-711.7* (364.9)	214.6 (344.6)	157 (356.3)	699.9*** (204.9)	731.5*** (211.2)
Year is 2012	4969.7*** (357.8)	3381.4*** (321.8)	1738.9*** (299.9)	1564.8*** (300.8)	3573.5*** (238.2)	3401.2*** (246.4)
Year is 2013	11335.4*** (504.8)	11402.3*** (491.9)	7114.3*** (336.6)	7130.0*** (328.9)	9928.3*** (278.8)	10395.7*** (277.9)
Year is 2014	-1330.6** (483.6)	1598.2*** (356.5)	1857.1*** (395.9)	2502.5*** (315.7)	3716.4*** (270)	4887.8*** (208.4)
Year is 2015	-957.1** (432.1)	-48.3 (465.2)	-1769.5*** (526.6)	-1131.1** (497.3)	-1428.4*** (242.9)	-512.8** (234.4)
Year is 2017	1160.6*** (326.3)	772.7** (321.1)	2997.9*** (267.5)	2846.7*** (273.3)	1298.0*** (202.1)	1558.2*** (238.3)
Year is 2018	-10228.6*** (489.7)	-10977.9*** (418.3)	-6314.4*** (325.5)	-5803.4*** (271.8)	-3841.0*** (255.1)	-3739.7*** (263)
Year is 2019	2516.4** (923.2)	-1014.5 (759.3)	609.1* (331.3)	-331.5 (320.3)	3280.4*** (271.9)	2789.9*** (239.7)
Constant	17116.1*** (1534.8)	31563.5*** (683.6)	21185.1*** (1121.5)	25386.2*** (499.6)	20716.7*** (814.3)	25613.2*** (377.9)
Observations	748	863	952	1092	844	985
R-squared	0.37	0.41	0.33	0.34	0.45	0.44

Note: Parentheses indicate standard errors. Twice-lagged consumption and lagged independent variables are employed as instruments. Single asterisk (*), double asterisks (**), and triple asterisks (***) represent statistical significance at the 10%, 5%, and 1% levels, respectively

Table 1.5: Marginal Propensity to Consume – 2018 and 2019 Aggregated

	Commercial		Intermediate		Residence	
	IV	OLS	IV	OLS	IV	OLS
Lag Consumption	0.60*** (0.028)	0.29*** (0.0082)	0.26*** (0.033)	0.19*** (0.0095)	0.29*** (0.021)	0.21* (0.0086)
Net farm income	0.0019*** (0.00035)	0.0035*** (0.00034)	0.029*** (0.0038)	0.026*** (0.0037)	-0.018*** (0.0021)	-0.0075* (0.0037)
Off-farm income	0.011*** (0.0021)	0.0099*** (0.0024)	0.032*** (0.0021)	0.033*** (0.0021)	0.030*** (0.0028)	0.039*** (0.0026)
MFP payments	0.066*** (0.016)	0.11*** (0.015)	0.18*** (0.025)	0.22*** (0.026)	0.62*** (0.083)	0.54*** (0.079)
Other government payments	0.082*** (0.0064)	0.093*** (0.0053)	0.20*** (0.023)	0.11*** (0.02)	0.100*** (0.029)	0.16*** (0.028)
Household net worth	0.00066*** (0.000086)	0.0010*** (0.0001)	0.0024*** (0.00015)	0.0028*** (0.00013)	0.0047*** (0.00023)	0.0046*** (0.00023)
Year is 2009	- -	-1894.0*** (390.4)	- -	-1536.3*** (346.6)	- -	1610.4*** (222.4)
Year is 2010	-384.4 (423.4)	-2077.4*** (407.4)	-170.8 (302.8)	-346.5 (320.8)	1765.5*** (168.1)	1693.7*** (166.4)
Year is 2011	836.3** (404.6)	-719.5* (366)	127.5 (359.5)	184.4 (355.7)	883.8*** (219.8)	886.4*** (224.3)
Year is 2012	5112.0*** (359.6)	3401.5*** (318)	1677.3*** (301.7)	1583.7*** (297)	3501.7*** (231.7)	3408.3*** (242.4)
Year is 2013	11313.8*** (518.8)	11418.5*** (502.9)	7183.7*** (323)	7164.1*** (322.5)	10205.7*** (272.6)	10525.7*** (278)
Year is 2014	-1753.9*** (528.5)	1573.6*** (385.3)	2307.9*** (360.1)	2666.1*** (308.9)	4385.3*** (243.4)	5066.5*** (211.8)
Year is 2015	-1099.7** (422.7)	-59.6 (459.3)	-1423.2*** (486.4)	-1068.5** (491.7)	-958.4*** (236.9)	-394.1 (237.2)
Year is 2017	1146.6*** (329.9)	748.3** (320.4)	2995.8*** (271.9)	2796.7*** (271.5)	1319.2*** (198.7)	1614.0*** (237)
Year is 2018	-5865.7*** (489.6)	-7061.2*** (427.8)	-4143.6*** (309.2)	-4137.0*** (273.7)	-1011.8*** (223.9)	-903.1*** (223.3)
Constant	15811.2*** (1553.2)	31585.3*** (632.2)	23183.8*** (1262.4)	25544.7*** (481.9)	22682.4*** (719.5)	25453.7*** (378.7)
Observations	685	797	874	1011	792	932
R-squared	0.35	0.41	0.34	0.34	0.45	0.44

Note: Parentheses indicate standard errors. Twice-lagged consumption and lagged independent variables are employed as instruments. Single asterisk (∗), double asterisks (∗∗), and triple asterisks (∗∗∗) represent statistical significance at the 10%, 5%, and 1% levels, respectively

Table 1.6: Marginal Propensity to Consume – Leverage Interactions

	Commercial		Intermediate		Residence	
	IV	OLS	IV	OLS	IV	OLS
Lag Consumption	0.82*** (0.054)	0.35*** (0.012)	0.30*** (0.04)	0.18*** (0.011)	0.44*** (0.029)	0.24*** (0.01)
Net farm income	0.00019 (0.0016)	0.0085*** (0.00097)	0.0061 (0.01)	0.013 (0.0082)	-0.0018 (0.011)	0.034*** (0.01)
Off-farm income	-0.036*** (0.0047)	-0.015*** (0.0033)	0.026*** (0.0035)	0.031*** (0.0032)	0.0067** (0.0024)	0.023*** (0.0027)
MFP payments in 2018	0.16*** (0.047)	0.34*** (0.031)	-0.19* (0.097)	0.18 (0.2)	1.59*** (0.14)	1.81*** (0.14)
MFP payments in 2019	-0.079*** (0.026)	-0.033* (0.017)	-0.41*** (0.085)	-0.43*** (0.086)	0.38* (0.2)	0.32* (0.18)
Other government payments	-0.004 (0.016)	0.10*** (0.011)	0.14*** (0.037)	0.19*** (0.033)	0.13*** (0.035)	0.20*** (0.043)
Household net worth	-0.001*** (0.0002)	0.0004*** (0.00013)	0.002*** (0.00032)	0.003*** (0.00022)	0.003*** (0.00036)	0.004*** (0.00033)
## Net farm income	0.0071* (0.0039)	-0.015*** (0.0018)	0.13** (0.063)	0.0086 (0.051)	-0.011 (0.087)	-0.29*** (0.084)
## Off-farm income	0.30*** (0.033)	0.14*** (0.021)	0.11** (0.042)	0.079** (0.038)	0.40*** (0.038)	0.21*** (0.037)
## MFP payments in 2018	0.18 (0.14)	-0.39*** (0.084)	1.59*** (0.42)	0.53 (0.84)	-3.03*** (0.56)	-3.49*** (0.52)
## MFP payments in 2019	0.28*** (0.069)	0.23*** (0.051)	1.00** (0.44)	1.60*** (0.38)	-3.48*** (0.63)	-2.25*** (0.56)
## Other gov payments	0.39*** (0.056)	-0.026 (0.039)	0.33 (0.3)	-0.67*** (0.23)	-1.39*** (0.49)	-1.87** (0.74)
## Household net worth	0.008*** (0.0008)	0.003*** (0.0004)	0.004 (0.003)	-0.001 (0.002)	0.018*** (0.003)	0.005 (0.004)
## Lag consumption	-1.16*** (0.11)	-0.22*** (0.042)	-0.22 (0.14)	0.15** (0.063)	-1.19*** (0.12)	-0.35*** (0.081)
Constant	17516.4*** (1562.6)	30279.4*** (680.4)	25695.0*** (501.3)	19675.1*** (901.1)	17516.4*** (1562.6)	30279.4*** (680.4)
Observations	744	857	948	1088	844	985
R-squared	0.37	0.43	0.34	0.35	0.45	0.45
Year fixed effects	yes	yes	yes	yes	yes	yes

Note: Parentheses indicate standard errors. Twice-lagged consumption and lagged independent variables are employed as instruments. Single asterisk (∗), double asterisks (∗∗), and triple asterisks (∗∗∗) represent statistical significance at the 10%, 5%, and 1% levels, respectively. Interactions with the debt to asset ratio are denoted by a double pound sign (##)

1.7 References

Carriker, G. L., M. R. Langemeier, T. C. Schroeder, and A. M. Featherstone. 1993. “Propensity to Consume Farm Family Disposable Income from Separate Sources”. *American Journal of Agricultural Economics*, 75(3):739.

Federal Reserve Bank of St. Louis. 2020. "Delinquency Rate On Loans To Finance Agricultural Production, All Commercial Banks". *Fred.Stlouisfed.Org*. https://fred.stlouisfed.org/series/DRFAPGACBN.

Girao, J. A., W. G. Tomek, and T. D. Mount. 1974. "The effect of income instability on farmers' consumption and investment." *The Review of Economics and Statistics* 56, no. 2: 141-149.

Hsieh, C. 2003. "Do consumers react to anticipated income changes? Evidence from the Alaska permanent fund." *American Economic Review* 93, no. 1: 397-405.

Ifft, J., K. Patrick, and A. Novini. 2014. “Debt use by US farm businesses, 1992-2011”. No. 1476-2016-120981.

Jodlowski, M. 2019. “Behind Every Farmer: Off-farm labor and farm viability”. Paper presented at NC-1177 annual meeting, Dallas TX, 8-9 October.

Kaplan, G., and G. L. Violante. 2014. "A model of the consumption response to fiscal stimulus payments." *Econometrica* 82, no. 4: 1199-1239.

Kaplan, G., G. L. Violante, and J. Weidner. 2014. “The wealthy hand-to-mouth”. No. w20073. National Bureau of Economic Research

Langemeier, M. R. and G. F. Patrick. 1990. “Farmers’ Marginal Propensity to Consume: An Application to Illinois Grain Farms”. *American Journal of Agricultural Economics*, 72(2):309.

Lewis, D. J., D. Melcangi, and L. Pilossoph. 2011. "Latent heterogeneity in the marginal propensity to consume." FRB of New York Staff Report 902

MacDonald, J. M., R. A. Hoppe, and D. Newton. 2018. “Three decades of consolidation in US agriculture”. No. 1476-2018-5467.

MacMillan, J. A., and R. M. A. Loyns. 1969. "A cross-section analysis of farm household expenditures." *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 17, no. 2: 92-105.

McKenzie, D. J. 2004. "Asymptotic theory for heterogeneous dynamic pseudo-panels." *Journal of Econometrics* 120, no. 2: 235-262.

Mishra, A. K. and C. L. Sandretto. 2002. “Stability of farm income and the role of nonfarm income in US agriculture”. *Applied Economic Perspectives and Policy*, *24*(1), 208-221.

Mishra, A. K., K. W. Erickson, J. M. Harris, C. B. Hallahan, and H. Uematsu. 2010. “Determinants of farm household income diversification in the United States: Evidence from farm-level data”. (No. 320-2016-9993).

Mullen, J. D., R. A. Powell, and B. F. Reece. 1980. "The Income and Consumption Experiences of a Sample of Farm Families." *Australian Journal of Agricultural Economics* 24, no. 3: 268-282.

Newton, J., and J. Sesenich. 2020. "Farm Bankruptcies Slow, More Aid Needed". *Fb.Org*. https://www.fb.org/market-intel/chapter12.

Sexton, R. J. 2013. "Market power, misconceptions, and modern agricultural markets." *American Journal of Agricultural Economics* 95, no. 2: 209-219.

US Census Bureau. 2020. "U.S. International Trade Data - Foreign Trade - US Census Bureau". *Census.Gov*. https://www.census.gov/foreign-trade/data/index.html.

USDA ERS. 2021. "2021 Farm Sector Income Forecast". *Ers.Usda.Gov*.

USDA FSA. 2018. "Market Facilitation Program". *Fsa.Usda.Gov*. https://www.fsa.usda.gov/programs-and-services/market-facilitation-program/.

USDA FSA. 2020. "Soybeans 2019 Export Highlights | USDA Foreign Agricultural Service". *Fas.Usda.Gov*. https://www.fas.usda.gov/soybeans-2019-export-highlights.

USDA NASS and USDA ERS, 2019 Agricultural Resource Management Survey.

Waugh, M. E. 2019. “The consumption response to trade shocks: Evidence from the US-China trade war”. No. w26353. National Bureau of Economic Research.

Whitaker, J. B. 2009. “The Varying Impacts of Agricultural Support Programs on U.S. Farm Household Consumption”. *American Journal of Agricultural Economics*, 91(3):569–580.

CHAPTER 2. THE VARIABILITY OF FARM HOUSEHOLD CONSUMPTION

2.1 Introduction

Inelastic demand for agricultural commodities results in large price fluctuations in response to variations in yield, which are themselves sensitive to the randomness inherent to natural processes. At the individual farm level these two sources of uncertainty - prices and yields - result in volatile farm incomes. A study of U.S. commercial farms over the 1997 to 2013 period found that while median farm income was $73,144, the median absolute change between years was $117,693, and farm incomes were negative in over 20 percent of years (Key et al. 2019). Most U.S. farm households who report farming as their primary occupation also receive incomes from more stable nonfarm sources, such as nonfarm labor, which adds some stability to their total incomes (Mishra and Sandretto 2002; Todd and Whitt 2019). Despite the volatile nature of farm incomes, there is a long-documented history of farm households exhibiting consumption smoothing behavior (Girao, Tomek, and Mount 1974; MacMillan and Loyns 1969; Mullen, Powel, and Reece 1980) as well as anticipatory saving (Chen et al. 1999). With effective consumption smoothing changes in incomes do not necessarily cause a change in well-being. So, incomes alone are not an appropriate measure of well-being and must be accompanied by an analysis of consumption.

There is a strand of research in the literature which examines how farm household consumption covaries with various income sources, but these studies largely fail to provide an analysis of consumption variability itself which is necessary to put their findings into context. Using a nationally representative sample of U.S. farm households over the 2000 to 2019 period we offer an in-depth analysis of farm household consumption variability which serves as a complement to prior studies of farm household incomes while also providing additional context to prior studies of farm household consumption. In quantifying consumption variability, we obtain several measures of household well-being which do not require the assumption of any specific utility function, only that volatility in consumption is undesirable. Additionally, we explore which farm and household characteristics, if any, are associated with consumption volatility.

The farm-related decisions of the farm household are inextricably linked to their nonfarm decisions and circumstances. Farm households are one example of where the firm and household are inseparable entities, and studies on farm household behavior may generalize well to households which own and operate other types of small businesses where incomes are highly variable and uncertain. Because of the important link between farm and nonfarm decisions we stratify our analysis by three distinct farm household typologies: commercial farms, intermediate farms, and residence farms. These three farm types allow us to examine the variability of household consumption as the household becomes increasingly focused on farm activities and less dependent on nonfarm incomes.

Despite the very modest consumption response to changes in incomes that has been documented in the literature (Whitaker 2009; Carriker et al. 1993; Langemeier and Patrick 1990), we show that the variability of real[1] consumption is rather sizable. In general, the consumption of commercial farm households exceeds that of residence farm households, which exceeds that of intermediate farm households, which is the same rank ordering as their total incomes. We find that for commercial farm households, increases in consumption are both more likely and larger in magnitude than decreases in consumption, with a statistically significant difference of $2,537. Intermediate and residence farm households on the other hand are more likely to experience a decrease in real consumption than an increase, and the difference between increases and decreases is not statistically significant.

We identify heterogeneity in the effect of farm income volatility and nonfarm income volatility on consumption volatility across commercial, intermediate, and residence farm households, which should be expected due to the differences in the composition of their total incomes. After controlling for the volatility of farm and nonfarm incomes and various farm and household characteristics there is a statistically significant difference in the consumption volatility across types of farm households: commercial farm households have consumption volatility that is about 14 percent less than that of intermediate farm households, and about 11 percent less than that of residence farm households. While numerous farm and household characteristics have been found to explain the volatility of farm, nonfarm, and total incomes (Key et al. 2019), we find only two characteristics are significant in explaining the consumption volatility of all farm typologies after controlling for income volatility. Owner-operators who are classified as a socially disadvantaged farmers or ranchers (SDFR), which we define as owner-operator respondents who

[1] Real values calculated with a 2018 base year using the GDP price deflator: https://fred.stlouisfed.org/series/GDPDEF

declare themselves to be non-white or female, have consumption volatility that is about 13 percent higher than non-SDFR owner-operator households on average. Specializing in the production of poultry is also associated with higher consumption volatility, with approximately 18 percent higher volatility than farms with other commodity specializations.

2.2 Data & Methodology

We utilize data from USDA's Agricultural Resource Management Survey (ARMS), an annually repeated cross-section which samples roughly 15,000 of the 2 million farms in the U.S. each year and collects information about the household of each family farm's principal operator. The National Agricultural Statistics Service (NASS) constructs observation weights such that each cross-section is representative of the total population of U.S. farm households. The usual method of calculating a volatility measure is to use a time-series of sequential observations from a specified population, such as an individual, to calculate a single value. Because ARMS is a randomly sampled repeated cross-section, sequential observations of the same household are uncommon. We follow Key et al. (2019) to overcome this limitation and instead calculate many values from non-sequential pairs of observations and correct the estimates for differences in the span and midyear between observations. We follow the methodology described by Key et al. (2019) as it provides a novel solution to the problem of non-sequential observations without using aggregation and allows us to use the ARMS dataset which is best suited for making generalizable findings about U.S. farm households.

Avoiding aggregation is critically important because it obscures much of the variability and results in estimates which are biased downwards if observations across individuals are not perfectly correlated. As explained by Gorbachev (2011), aggregate volatility can be decomposed into two parts, average household volatility plus the average covariance between households. If the average covariance between households' consumption spending falls then aggregate volatility could decrease even if the average household volatility increased. Therefore, to measure the volatility of consumption in a manner which is reflective of that experienced by individual households it is necessary to use data at the household level and avoid aggregation entirely.

As described by Key et al. (2019), many common measures of volatility become nonsensical when income or average income are negative, and to accommodate for this they report several volatility measures which allow for meaningful interpretations even in the event of negative values. Even though consumption spending cannot be negative, we calculate and report many of the same metrics so that the volatility of consumption and incomes can be compared. The volatility measures examined are the absolute change between years, absolute arc percentage change (AAPC), absolute coefficient of variation (ACV), and standard deviation of arc percentage change (SDAPC).

The absolute change between years, $ABSCHG_{ist} = |c_{is} - c_{it}|$, where c_{is} and c_{it} are real consumption of household *i* in years *s* and *t*, is a useful measure of variability because of the ease of its interpretation. The main drawback of using absolute change is that the relative magnitude of the same value changes when looking across populations with different means. There is an important difference between a change from 30,000 to 31,000 and a change from 130,000 to 131,000, which absolute change between years does not capture.

To account for differences in means, we calculate the absolute value of the arc percentage change, $AAPC_{ist} = 100 * \left|\frac{c_{it}-c_{is}}{\bar{c}_i}\right|$, where $\bar{c}_i$ is average real consumption of household *i* in years *s* and *t*. This measure is easily compared across populations because each observation's value is scaled by their mean. The absolute arc percentage change is interpreted similarly to the percentage change, except that the arc percentage change is symmetric in increases and decreases. The absolute value of the arc percentage change is bounded by 0 and 200 when both values take the same sign, taking the value of 0 if both observations are the same and 200 if either observation is 0.

Another measure that accounts for differences in means but is unbounded, allowing for large values even when the mean is very small, is the absolute coefficient of variation, $ACV_{ist} = \left|\frac{\sqrt{(c_{is}-\bar{c}_i)^2+(c_{it}-\bar{c}_i)^2}}{c_i^-}\right|$, (the standard deviation scaled by the mean). Similar to the arc percentage change, the absolute coefficient of variation allows for negative values, but is unbounded. The ACV is easy to interpret, with large values implying that variability is large relative to the mean, and small values implying that variability is small relative to the mean.

To measure the volatility across the entire sample we also calculate the standard deviation of arc percentage change, $SDAPC_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(APC_{it} - \overline{APC_t})^2}$, where $APC_{ist} = \frac{(c_{it}-c_{is})}{0.5*(|c_{it}|+|c_{is}|)}$, and N is the total number of households in the sample.

Farm households may be more reliant on farm or nonfarm incomes depending on which activities they dedicate most of their time and the scale of their farming operation. Because of this, we separate farm households into three distinct groups for our analysis: commercial, intermediate, and residence farms. We define commercial farms as those that have gross cash farm incomes greater than $350,000 in real 2018 dollars. Residence farms are those with gross cash farm incomes of less than $350,000 in real 2018 dollars, and where the primary occupation of the owner-operator is either not farming or they are retired from farming. Intermediate farms are essentially small commercial farms, the primary occupation of the owner-operator is farming, but with gross cash farm incomes of less than $350,000.

Certain observations are omitted from our analysis. We only include family farms which are sole-proprietors or partnerships, C-corps, S-corps, or other such entities where the proportion of business income owned by the household responding to the survey may be obscured are excluded. We also omit what are referred to as limited-resource farms, which have two sequential years of low farm sales and low household income. To ensure that we are correctly matching the same households between cross-sections, we omit any farm where the difference in the reported operator age is greater than the span between observations plus 2. We also only examine pairs of observations where the span of the two observations is 5 or fewer years. Because of the stratified sampling nature of ARMS, and smaller farms being more numerous than larger farms, the likelihood of ARMS surveying the same farm again gets increasingly small as the size of the farm gets smaller. Because of this, our sample of commercial farms is larger than that of intermediate farms, which is larger than the sample of residence farms. Additionally, because of possible differences in the likelihood of survival, the distribution of spans differs by farm typology. Table 2.1 tabulates the sample by farm typology and span.

To aid in comparing our calculated volatility measures to other studies using time series data with a span of 1, and across our farm typologies which have differing distributions of span, we report two additional statistics in addition to the mean values of our volatility measures. We report the means of the subset where the span is equal to 2, as well as the predicted value calculated using a midyear of 2010 and span of 1 by using the following regression equation:

$$V_{ist} = b_0 + b_1\gamma_{ist} + b_2\psi_{ist} + \epsilon \tag{2.1}$$

where V is the volatility measure, γ is the span and ψ is the midyear between observations of household i in year s and t.

For all estimated means and standard errors we use the mean of the two observation weights constructed by the National Agricultural Statistics Service (NASS) and a bootstrap procedure. The levels and volatility of consumption for commercial, intermediate, and residence farm households are reported in Table 2.3, Table 2.4, and Table 2.5, respectively.

We empirically test for asymmetry in the absolute change in consumption between years with the following equation:

$$ABSCHG_{ist} = b_0 + b_1\gamma_{st} + b_2\psi_{st} + b_3\delta_{ist} + \epsilon \tag{2.2}$$

where δ_{ist} is an indicator for whether the absolute change in consumption between year s and year t of household i was an increase or not, to make our results comparable to other studies that most commonly use data with a span of 1 we include controls for the. We estimate the above equation individually for each farm typology and report the results in Table 2.5.

The absolute coefficient of variation allows for the efficient comparison of volatility across samples with different means, and this feature is very important as average consumption levels are very different across commercial, intermediate, and residence farm households. We use the ACV as the independent variable in a multivariate regression to analyze the determinants of consumption volatility. As the ACV is unbounded and allows for very large values when the mean is near zero, it is heavily skewed. Because of this, we use a log transform in our models which has the added benefit of being able to interpret regression coefficients as a percentage change. In addition to various farm and household characteristics, we include the log coefficient of variation of farm income and nonfarm income, yielding the following equation:

$$lnACV_{ist} = b_0 + b_1\gamma_{st} + b_2\psi_{st} + \beta X_{ist} + \epsilon \tag{2.3}$$

where X_{ist} is a vector of characteristics of farm household i, β is a vector of regression coefficients, and we again include controls for the span γ and midyear ψ between the observations used to calculate the volatility measure.

The farm and household characteristics which we examine are state, commodity specialization, marital status in the first observation year, age, household wealth, college education, number of household members, difference in the population interaction index, whether the owner-operator is a socially disadvantaged farmer or rancher, and the logged ACV of both farm and nonfarm incomes.

Commodity specialization and state are useful for identifying like farms. Marital status, number of household members, age, and education are all plausibly associated with differences in preferences and risk attitudes which may affect the household's desire to reduce consumption variability and maintain a smooth consumption pattern. Household wealth and the difference in the population interaction index are all likely associated with the household's ability to reduce consumption variability with either savings or nonfarm employment. The population interaction index gives a cardinal value of closeness to large population centers, and the difference between the 1990 and 2000 index values offers a measure of growth in nonfarm employment opportunities. Owner-operator status as a socially disadvantaged farmer or rancher (SDFR) is useful for answering important questions related to equity. Definitions of SDFR vary by organization, program, and study, and we use the broad definition of any owner-operator who self-identifies as non-white and/or a woman. The final two variables, the logged ACV for farm and nonfarm incomes, both measure relative risks to consumption variability.

We estimate Equation 2.2 jointly on all farm typologies with the inclusion of an additional indicator variable for status as an intermediate or residence farm, the coefficient on the indicator variables testing the hypothesis that intermediate and residence farms have differences in their consumption volatility compared to commercial farms after controlling for other factors. We also estimate Equation 2.2 in the manner described above but with the inclusion of indicators for commercial, intermediate, and residence farms interacted with logged ACV of farm and nonfarm incomes – allowing unique parameters for both farm and nonfarm income volatility for each of the three farm typologies, but common parameters for all other variables. We also estimate Equation 2.2 individually on each of the three farm typologies. The results of these five models are reported in Table 2.7.

2.3 Results

Table 2.3, Table 2.4, and Table 2.5, report the average levels of consumption as well as consumption variability for the sample of commercial, intermediate, and residence farm households respectively. The second column reports the values of the variable calculated using the full sample of paired observations. The third column reports the 95% confidence interval of any reported means. The fourth column reports the predicted value from a linear regression of the volatility measure on span and midyear, using a midyear of 2010 and a span of 1. The predicted value is useful in the case that variability may be increasing or decreasing over time, such as the magnitudes of changes between years are likely increasing as the span between surveys increases, and for comparing across farm typologies as they have differing distributions of span and midyear. For that same reason, the fifth column reports the value calculated using only a subsample with a span of 2 years between surveys.

The median consumption of commercial farm households is $52,796, while that of intermediate farm households is $35,750, and that of residence farm households is $40,750. For all three farm typologies the predicted value and the span of 2 subset yield medians which are similar to that of their full sample median.

Mean consumption of commercial farm households is $57,882, that of intermediate farm households is $41,142, and that of residence farm households is $49,004. The predicted value and the span of 2 subset are closest to the mean of the full sample for commercial farms and are farthest from the mean of the full sample for residence farms. Residence farm households also have the largest difference between the mean and median implying that their consumption has the most positively skewed distribution.

The median absolute change between years of commercial farm households is $19,208 (36% of median consumption), while that of intermediate farm households is $15,520 (47% of median consumption), and that of residence farm households is $16,670 (40% of median consumption). Prior studies have shown that non-farm households have a median absolute change in their incomes equal to roughly 25% of median income, while for commercial farm's the median absolute change is over 103% of median income (Hertz 2006; Key et al. 2019). The mean absolute change between years is $27,586 for commercial farm households (48% of mean consumption), $21,163 for intermediate farm households (51% of mean consumption), and $24,447 for residence farm households (50% of mean consumption).

The share of farms that saw an increase in consumption was 51.87% for commercial farm households, 47.34% for intermediate farm households, and 48.89% for residence farm households. These results might sound surprisingly low. Loss aversion and consumption smoothing are the basis of many influential economic models derived from simple assumptions of decreasing marginal utility, and so one might expect that farm households would most commonly experience an increase in consumption if any change at all. When using nominal values instead of real values, increases comprise 58.6%, 52.4%, and 54.3% of observed changes in consumption. What is perhaps more surprising is that the share of changes in real consumption which are increases is smaller than the share of farm, nonfarm, and total incomes changes that are increases for all typologies with only one exception – the total income of intermediate farm households. We observe commercial farm households having in increase in their real farm, nonfarm, and total incomes in 56.6%, 53.0%, and 56.4% of observed changes. For intermediate farm households, the proportions of changes in real farm, nonfarm, and total incomes which are increases are 47.6%, 48.9%, and 44.7% respectively, and for residence farm households those proportions are 53.7%, 50.2%, and 52.1% respectively. It's interesting to note that for intermediate farms total income is less likely to increase than either farm income or nonfarm income individually. Looking at the predicted value and span of 2 subset for the share of changes in consumption which are increases is important due to the differences in the samples. While the share of increases is largest for commercial farm households in the full sample, after controlling for span and midyear residence farm households have the largest share, followed by commercial and intermediate farm households.

Table 2.5 reports the correlations of real consumption, farm income, nonfarm income, and total income by farm type. The correlations highlight the relative importance of farm and nonfarm incomes for the three farm types, and also reveals why intermediate farm total incomes increase less often than either of its two components. Farm income and nonfarm income are positively correlated for commercial farms but are negatively correlated for intermediate and residence farms. This negative correlation is why total income may increase less often than either of its two components for intermediate farms. While residence farms have an even larger negative correlation, the relative size of farm income compared to total income is considerably smaller for residence farms and so they do not experience the same effect.

Separating the absolute change in consumption into increases and decreases highlights an asymmetry in changes in consumption. For all farm types the median increase in consumption is larger in magnitude than the median decrease, and except for intermediate farm households, the mean increase in consumption is larger in magnitude than the mean decrease. The difference between increases and decreases in consumption across farm typology is interesting as it hints at possible disparate consumption behavior of farm and nonfarm households. A histogram of changes in consumption for each farm type, as shown in Figure 2.1, illustrates the absolute magnitude of consumption volatility as well as differences in skewness.

Table 2.6 shows the results of estimating Equation 1.2. The results indicate that there is not a statistically significant difference between increases and decreases in consumption for residential or intermediate farm households. However, commercial farm households have increases in consumption which are estimated to be $2,537 larger than their decreases in consumption, and this result is statistically significant at the 99% confidence level. Though this result is not a direct test, it suggests that commercial farm households may have asymmetric consumption responses to incomes shocks. Asymmetric consumption responses to positive and negative income shocks have been observed in nonfarm households (Bunn et al. 2017) as well as in GDP per capita (Apergis and Miller 2006), with possible explanations varying from liquidity constraints to behavioral phenomena such as mental accounting (Baugh et al. 2020).

The mean ACV of consumption is largest for intermediate farm households at 0.344, followed by commercial farm households at 0.340, and smallest for residence farm households at 0.331. For comparison, Key et al. (2019) estimated the mean ACV for farm and nonfarm incomes to be 1.37 and 0.68 for commercial farms over the 1997-2013 period. Key et al. (2019) also document a downward trend in the ACV of farm, nonfarm, and total incomes. Figure 2.2 shows the mean ACV of the three farm types by the midyear of observations and their trend lines. While intermediate and residence farm households have a downward trend in the volatility of their consumption, commercial farm households do not. Instead, the mean ACV of commercial farm households' consumption appears to take a form similar to that of charts plotting farm sector incomes, particularly the pronounced increase surrounding the 2012-2013 North American drought.

The mean AAPC takes the same rank ordering of mean ACV. The mean AAPC of commercial farm households is 48.122, while that of intermediate farm households is 48.638, and that of residence farm households is 46.857. The standard deviation of arc percentage change are 61.521, 65.019, and 62.346 respectively. For comparison, in an examination of commercial farms the mean AAPC of farm and nonfarm income has been estimated to be 126.9 and 95.9, and the SDAPC of 143.5 and 110.4 (Key et al. 2019), and for nonfarm households estimates of the standard deviation of APC in income vary between 30 and 50 (Dynan et al. 2012; Dahl et al. 2011).

The results of the determinant analysis described in Equation 1.3 are reported in Table 2.7. A consistent result is that while commonly statistically significant, the effect of income volatility on consumption volatility is economically small. In the first model, we find that a 10% increase in the volatility of farm income is associated with an increase in consumption volatility of about 0.27% (statistically significant at the 95% confidence level), while a 10% increase in the volatility of nonfarm income is associated with an increase in consumption volatility of approximately 0.86% (statistically significant at the 99% confidence level). Households operating poultry farms have consumption volatility that is approximately 18.5% higher than the omitted base category of corn, soybean, and sorghum farms (statistically significant at the 95% confidence level), all else constant. Additionally, SDFR owner-operators are estimated to have consumption volatility that is about 13% higher than non-SDFR owner-operators (statistically significant at the 90% confidence level), a finding which is important but not necessarily surprising given historical disparity in consumption volatility found by others. Keys (2008) found that for each decade between 1970 and 2000 the annual real food consumption of households headed by black women was more volatile than that of white women, which was more volatile than that of black men, which was more volatile than that of white men. A more recent study found that the consumption response of black and Hispanic households was 50 and 20 percent higher than those of white households experiencing similarly sized income shocks, and that the disparity is attributable to differences in liquid wealth (Ganong et al. 2020).

The second model allows for commercial, intermediate, and residence farm households to have disparate effects of farm and nonfarm income volatility. For commercial farms, only farm income volatility is statistically significant at the 99% confidence level, with a 10% increase being associated with an increase in consumption volatility of 0.25%. For both intermediate and residence farm households the effect on farm income volatility is not statistically significant at the 99% confidence level, but the effects of nonfarm income volatility are both highly significant with similarly sized effects with a 10% increase being associated with 0.86% increase in consumption volatility. After controlling for farm and household characteristics, as well as the disparate effects of farm and nonfarm income volatility, residence farm households have consumption volatility which is estimated to be 15% larger than that of commercial farm households, and intermediate farm households have consumption volatility that is estimated to be about 13% larger than that of commercial farm households. The differences among poultry farms and by SDFR status are similar to those of the first model.

The third, fourth, and fifth models are calculated by estimating Equation 1.2 on the commercial, intermediate, and residence farm samples individually. The results of these models indicate that the differences among poultry farms may largely stem from the intermediate farm sample. Similarly, the differences among SDFR status may largely come from the residence farm sample, although that may have to do with the intermediate and commercial farm samples having relatively fewer SDFR observations, with SDFR observations. SDFR observations are 12.0%, 8.9%, and 4.5% of the residence, intermediate, and commercial farm samples, respectively.

While almost all the farm and household characteristics are not statistically significant in explaining consumption volatility across each of our models, farm and household characteristics are highly significant in explaining the volatility of farm, nonfarm, and total incomes of commercial farms (Key et al. 2019). While many farm and household characteristics are likely associated with differences in preferences, risk tolerance, and relative abilities to smooth consumption, these differences largely do not appear to manifest into distinguishable differences in consumption volatility.

2.4 Conclusions

Despite having volatile income from farming, farm household's consumption response to changes in incomes have consistently been estimated to be very small. The results of these studies usually indicate that the variability in consumption is small, but they largely fail to directly examine the magnitude of consumption variability outside of its covariance with income. We provide a more focused analysis of consumption variability which provides additional context for the findings of previous studies.

We use pairs of non-sequential observations from a nationally representative repeated cross-section of farm households over 2000 to 2019 to measure consumption variability. This non-sequential observation approach is necessary to avoid using aggregate measures of consumption which are likely not representative of household level variability.

We find that the average levels of consumption are higher for commercial farm households than that of intermediate or residence farm households. After controlling for the volatility of farm and nonfarm incomes and lower average income, we find that the consumption of residential and intermediate farm households are more volatile than that of commercial farm households. While the variability of consumption is significantly less than the variability of incomes in terms several different volatility measures, we that real consumption increases less often than real farm and nonfarm incomes, and in more than half of observed changes real consumption decreases. Commercial farm households are more likely to experience an increase in real consumption than intermediate or residence farm households, and there is statistically significant asymmetry between their increases and decreases in consumption, with increases being $2,537 larger than decreases.

While numerous farm and household characteristics are highly significant in explaining the volatility of farm, nonfarm, and total incomes of U.S. commercial farms (Key et al. 2019), we find that farm and household characteristics are very poor at explaining consumption volatility after controlling for income volatility. After controlling for income volatility, we estimate that consumption volatility is about 12.7% higher for intermediate farm households than commercial farm households, and about 15% higher for residence farm households than commercial farm households. One notable exception to the insignificant farm and household characteristics is status as a socially disadvantaged farmer or rancher, which are estimated to have consumption that is around 15% more volatile than non-SDFR owner-operators.

Farm and nonfarm income volatility are positively associated with consumption volatility, but the estimated effects are very small. This finding combined with those of prior studies showing that large changes in incomes result in small changes in consumption might lead one to believe that consumption is very stable, and while we find that consumption is far less variable than incomes, the magnitude of consumption variability is still notable. Among commercial farm households for example, the median of consumption is $52,796, while the median absolute change between years is $19,208 (or 36% of the median). A five-figure change in real consumption is quite common, occurring in over two-thirds of all observed changes.

It appears that farm household consumption may be considerably noisier than alluded to by prior studies. We posit that this considerable noise is a testament to the difficulty of modeling human behavior and has a rather simple explanation. Just about any standard mathematical function that could be used to model utility will result in any sudden spike in consumption being interpreted as an inefficient allocation of resources that should have been smoothed over time. But, that apparent randomness may in fact be a part of a utility maximizing consumption bundle. A family who saves regularly for a less-than-annual vacation may appear to have a nonsensical consumption pattern and be experiencing some sort of inability to smooth their consumption, despite that consumption pattern being a deliberate utility maximizing decision. It may be useful to think of consumption volatility as having two components, undesirable volatility which is due to some fiscal constraint or uncertainty which causes an inability for the household to smooth consumption in a manner that they otherwise would, and agnostic volatility which is simply due to the temporal peculiarities of the household's desires. The existing body of evidence on the relationship between farm household incomes and consumption would imply that the first undesirable component is relatively small, while our findings would imply that the second agnostic component is quite large.

Table 2.1: Span of Non-Sequential Observation Pairs

	Farm Typology			
Span	Commercial	Intermediate	Residential	Total
1	1,305	527	665	2,400
2	6,471	3,746	2,108	12,034
3	3,961	2,447	1,127	7,409
4	3,226	1,978	899	6,023
5	2,587	1,781	751	5,119
Total	17,550	10,479	5,550	32,985

Table 2.2: Consumption and Consumption Variability of Commercial Farms

	Full sample (span = 1-5)	95% confidence interval	Predicted value (span = 1, midyear = 2010)	Span = 2
Median	52,796		52,681	52,709
Mean	57,882	[56,892 – 58,871]	57,939	56,645
Median absolute change between years	19,208		18,279	18,214
Mean absolute change between years	27,586	[26,866 – 28,305]	27,660	26,599
Share which are increases	51.87%		48.83%	48.60%
Median increase	20,732		19,564	19,506
Mean increase	28,758	[27,665 – 29,852]	28,790	27,453
Median decrease	17,904		16,877	16,509
Mean decrease	26,323	[25,400 – 27,245]	26,549	25,809
Mean ACV	0.340	[0.334 – 0.347]	0.329	0.327
Mean AAPC	48.122	[47.191 – 49.052]	46.566	46.220
Std. dev. Arc percentage change	61.521		n.a.	59.737
Observations	17,550		17,550	6,471

Table 2.3: Consumption and Consumption Variability of Intermediate Farms

	Full sample (span = 1-5)	95% confidence interval	Predicted value (span = 1, midyear = 2010)	Span = 2
Median	35,750		35,843	36,262
Mean	41,142	[39,903 – 42,381]	40,341	43,305
Median absolute change between years	15,520		14,217	14,776
Mean absolute change between years	21,163	[19,862– 22,463]	20,317	20,714
Share which are increases	47.34%		46.38%	47.04%
Median increase	15,786		14,788	15,127
Mean increase	20,174	[18,741 – 21,608]	18,414	20,293
Median decrease	15,200		13,523	14,686
Mean decrease	22,050	[20,082 – 24,020]	22,029	21,088
Mean ACV	0.344	[0.328 – 0.359]	0.328	0.321
Mean AAPC	48.638	[46.504 – 50.772]	46.416	45.444
Std. dev. Arc percentage change	65.019		n.a.	63.405
Observations	10,479		10,479	3,746

Table 2.4: Consumption and Consumption Variability of Residence Farms

	Full sample (span = 1-5)	95% confidence interval	Predicted value (span = 1, midyear = 2010)	Span = 2
Median	40,750		41,003	39,748
Mean	49,004	[44,162 – 53,845]	51,290	45,431
Median absolute change between years	16,670		15,199	16,371
Mean absolute change between years	24,447	[21,157 – 27,738]	24,375	22,401
Share which are increases	48.89%		50.41%	49.30%
Median increase	16,821		15,182	16,655
Mean increase	25,261	[19,192 – 31,331]	26,535	21,221
Median decrease	16,484		15,376	16,090
Mean decrease	23,668	[20,556 – 26,780]	22,716	23,549
Mean ACV	0.331	[0.316 – 0.346]	0.312	0.323
Mean AAPC	46.857	[44.729 – 48.985]	44.184	45.711
Std. dev. Arc percentage change	62.346		n.a.	61.092
Observations	5,550		5,550	2,108

Table 2.5: Correlation Matrices

Commercial	Consumption	Farm Income	Nonfarm Income	Total Income
Consumption	1.0000			
Farm Income	0.1309	1.0000		
Nonfarm Income	0.1048	0.0385	1.0000	
Total Income	0.1543	0.9570	0.3268	1.0000
Intermediate				
Consumption	1.0000			
Farm Income	0.0112	1.0000		
Nonfarm Income	0.0841	-0.0243	1.0000	
Total Income	0.0757	0.5715	0.8065	1.0000
Residence				
Consumption	1.0000			
Farm Income	-0.0034	1.0000		
Nonfarm Income	0.2322	-0.0474	1.0000	
Total Income	0.2250	0.2343	0.9600	1.0000

Table 2.6: Asymmetry in Absolute Change Between Years in Consumption

	Commercial	Intermediate	Residential
Span	-99.5 (339.9)	517.6 (479.9)	-241.3 (1,311.8)
Midyear	205.5*** (77.3)	-184.7 (124.3)	-912.5** (404.7)
Increase (1/0)	2,537.7*** (746.65)	-1,830.1 (1,166.2)	2,054.6 (3,527.4)
Constant	-386,482.2** (155,588.4)	391,850.2 (250,121.1)	1,857,793** (816,025.8)
Observations	14,550	10,479	5,550
R-squared	0.003	0.003	0.019

Table 2.7: Regressions on Volatility of Consumption

	All Farms (1)	All Farms (2)	Commercial	Intermediate	Residence
	c_lnacv	c_lnacv	c_lnacv	c_lnacv	c_lnacv
fi_lnacv	0.028**		0.026***	-0.0019	0.041**
	(0.012)		(0.0089)	(0.015)	(0.021)
ofi_lnacv	0.090***		0.017	0.11***	0.11***
	(0.015)		(0.010)	(0.020)	(0.023)
Commercial # fi_lnacv		0.026***			
		(0.0098)			
Intermediate # fi_lnacv		-0.0043			
		(0.017)			
Residence # fi_lnacv		0.045**			
		(0.021)			
Commercial # ofi_lnacv		0.024**			
		(0.011)			
Intermediate # ofi_lnacv		0.10***			
		(0.022)			
Residence # ofi_lnacv		0.10***			
		(0.024)			
Intermediate	0.047	0.12***			
	(0.039)	(0.042)			
Residence	0.048	0.14**			
	(0.046)	(0.062)			
SDFR	0.12*	0.12*	0.072	0.020	0.20**
	(0.068)	(0.067)	(0.088)	(0.094)	(0.095)
DPII	0.00000086	0.00000057	0.0000071*	0.0000095	-0.00000087
	(0.000013)	(0.000013)	(0.0000040)	(0.0000077)	(0.000016)
Span	0.050***	0.050***	0.032***	0.046**	0.064**
	(0.014)	(0.014)	(0.012)	(0.021)	(0.026)
Midyear	-0.017***	-0.017***	-0.0078***	-0.020***	-0.017**
	(0.0039)	(0.0039)	(0.0026)	(0.0056)	(0.0065)
Age 50 - 65	-0.024	-0.028	0.039	-0.096	-0.041
	(0.057)	(0.056)	(0.040)	(0.084)	(0.082)
Age > 65	-0.078	-0.084	0.085	-0.20**	-0.11
	(0.061)	(0.061)	(0.052)	(0.095)	(0.10)
College	-0.070	-0.073	-0.011	-0.10	-0.091
	(0.046)	(0.046)	(0.033)	(0.065)	(0.078)
Married in year 1	0.012	0.011	-0.15***	0.040	0.037
	(0.072)	(0.071)	(0.053)	(0.12)	(0.10)

*Standard errors in parentheses * p<0.1 ** p<0.05 *** p<0.01*

Table 2.7: continued

Hhsize = 2	0.054	0.054	-0.021	0.011	0.067
	(0.088)	(0.088)	(0.064)	(0.12)	(0.13)
Hhsize = 3	0.13	0.13	0.019	-0.020	0.24*
	(0.092)	(0.092)	(0.068)	(0.13)	(0.13)
Hhsize = 4+	0.031	0.031	-0.057	-0.062	0.059
	(0.099)	(0.099)	(0.069)	(0.14)	(0.14)
Wealth 500k – 1.25m	-0.0067	-0.0081	-0.059	-0.065	0.050
	(0.050)	(0.050)	(0.067)	(0.076)	(0.067)
Wealth 1.25m – 2.0m	-0.020	-0.023	-0.041	-0.082	0.051
	(0.061)	(0.061)	(0.061)	(0.082)	(0.089)
Wealth 2.0m+	0.042	0.043	-0.034	0.029	0.11
	(0.058)	(0.058)	(0.055)	(0.078)	(0.11)
Barley oats and wheat	0.050	0.051	0.013	0.062	0.019
	(0.075)	(0.075)	(0.054)	(0.14)	(0.32)
Miscellaneous crops	0.049	0.049	-0.098*	-0.023	0.13
	(0.072)	(0.072)	(0.053)	(0.13)	(0.13)
Fruits and nuts	0.15	0.16	-0.11	0.16	0.31
	(0.15)	(0.15)	(0.077)	(0.20)	(0.31)
Vegetables and nursery	0.095	0.094	-0.079	-0.098	0.37*
	(0.11)	(0.11)	(0.080)	(0.18)	(0.22)
Beef cattle	-0.035	-0.027	-0.059	0.13	-0.0092
	(0.10)	(0.10)	(0.077)	(0.14)	(0.16)
Hogs and other livestock	0.054	0.055	0.071	0.090	0.11
	(0.064)	(0.063)	(0.072)	(0.100)	(0.12)
Poultry	0.17**	0.16**	0.019	0.19**	0.33
	(0.079)	(0.078)	(0.073)	(0.096)	(0.20)
Dairy	-0.0088	-0.011	-0.026	0.025	-0.26
	(0.061)	(0.060)	(0.055)	(0.11)	(0.44)
Switched	0.054	0.056	0.012	0.084	0.084
	(0.056)	(0.056)	(0.046)	(0.087)	(0.12)
Constant	31.8***	32.0***	14.5***	39.4***	31.3**
	(7.87)	(7.94)	(5.30)	(11.3)	(13.1)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	31671	31671	16201	9967	5503
R-squared	0.05	0.05	0.02	0.07	0.08

*Standard errors in parentheses * p<0.1 ** p<0.05 *** p<0.01*

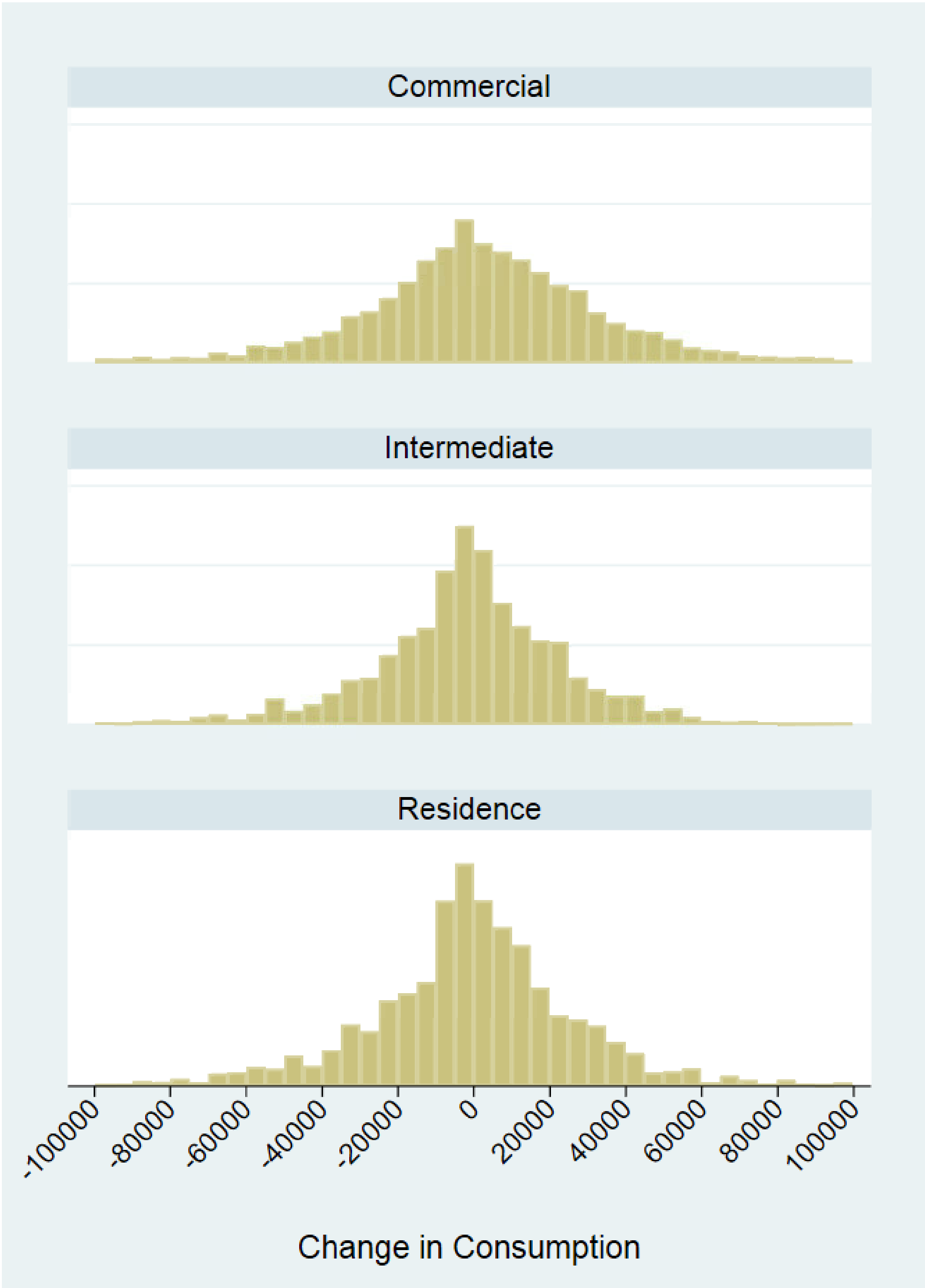

Figure 2.1: Histogram of Changes in Real Consumption

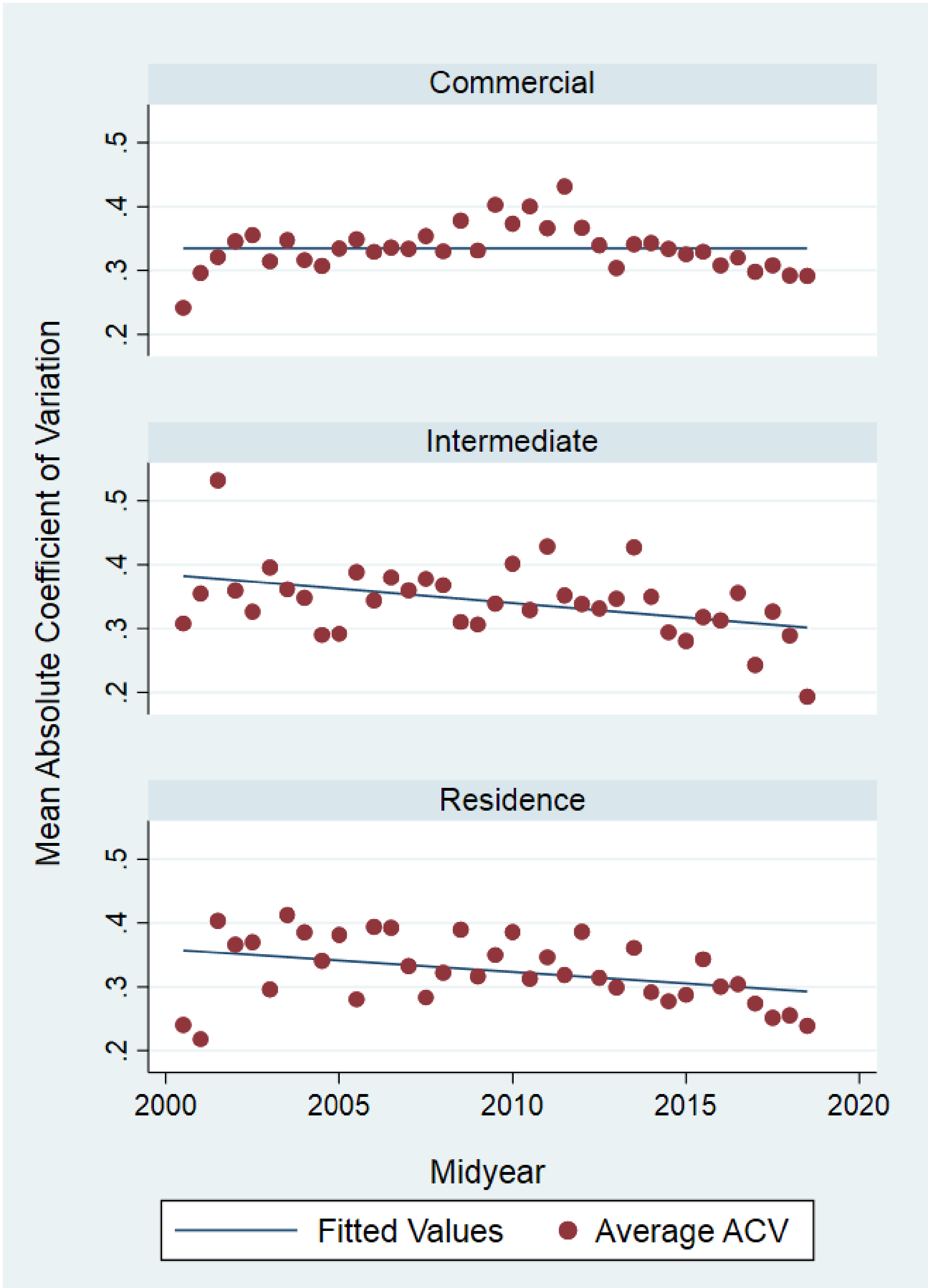

Figure 2.2: Average ACV by Midyear

2.5 References

Apergis, N., and S. M. Miller. "Consumption asymmetry and the stock market: empirical evidence." Economics letters 93, no. 3 (2006): 337-342.

Baugh, B., I. Ben-David, P. Hoonsuk, J. Parker. 2020. “Charles A. Dice Center for Research in Financial Economics,” 64.

Bunn, P., J. Le Roux, K. Reinold, and P. Surico. 2018. “The Consumption Response to Positive and Negative Income Shocks.” Journal of Monetary Economics 96 (June): 1–15. https://doi.org/10.1016/j.jmoneco.2017.11.007.

Carriker, G. L., M. R. Langemeier, T. C. Schroeder, and A. M. Featherstone. 1993. “Propensity to Consume Farm Family Disposable Income from Separate Sources”. American Journal of Agricultural Economics, 75(3):739.

Chen, K., Meilke, K., Turvey, C. 1999. “Income Risk and Farm Consumption Behavior.” Agricultural Economics 20 (2): 173–83. https://doi.org/10.1016/S0169-5150(98)00079-6.

Dahl, M., T. DeLeire, and J. Schwabish. 2011. Estimates of Year-to-Year Volatility in Earnings and in Household Incomes from Administrative, Survey, and Matched Data. Journal of Human Resources 46 (4): 750–74.

Dynan, K., D. Elmendorf, and D. Sichel. 2012. The Evolution of Household Income Volatility. The B.E. Journal of Economic Analysis and Policy 12 (2): 1–40.

Ganong, P., D. Jones, P. Noel, F. Greig, D. Farrell, and C. Wheat. 2020. "Wealth, race, and consumption smoothing of typical income shocks." NBER Working Paper w27552.

Gorbachev, Olga. (2011). Did Household Consumption Become More Volatile? American Economic Review 101 (5): 2248–70. https://doi.org/10.1257/aer.101.5.2248.

Hertz, T. 2006. Understanding Mobility in America. The Center for American Progress. Discussion Paper.

Key, N., D. L. Prager, and C. B. Burns. 2018. The Income Volatility of U.S. Commercial Farm Households. Applied Economic Perspectives and Policy 40(2), 215–239.

Key, N., M. Roberts, and E. O’Donoghue. 2006. Risk and Farm Operator Labour Supply. Applied Economics 38(5): 573–86. https://doi.org/10.1080/00036840500369043.

Keys, B. 2008. “Trends in Income and Consumption Volatility: 1970-2000.” In Income Volatility and Food Assistance in the United States, edited by Dean Jolliffe and James P. Ziliak, 11–34. W.E. Upjohn Institute. https://doi.org/10.17848/9781435684126.Ch2.

Girao, J. A., W. G. Tomek, and T. D. Mount. 1974. "The effect of income instability on farmers' consumption and investment." The Review of Economics and Statistics 56, no. 2: 141-149.

Mishra, A. K. and B. K. Goodwin. 1998. Income risk and allocation of labour time: an empirical investigation. Applied Economics 30(12), 1549–1555.

Langemeier, M. R. and G. F. Patrick. 1990. “Farmers’ Marginal Propensity to Consume: An Application to Illinois Grain Farms”. American Journal of Agricultural Economics, 72(2):309.

MacMillan, J. A., and R. M. A. Loyns. 1969. "A cross-section analysis of farm household expenditures." Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 17, no. 2: 92-105.

Mishra, A. K. and C. L. Sandretto. 2002. “Stability of farm income and the role of nonfarm income in US agriculture”. Applied Economic Perspectives and Policy, 24(1), 208-221.

Mullen, J. D., R. A. Powell, and B. F. Reece. 1980. "The Income and Consumption Experiences of a Sample of Farm Families." Australian Journal of Agricultural Economics 24, no. 3: 268-282.

USDA NASS and USDA ERS, 2019 Agricultural Resource Management Survey.

Whitaker, J. B. 2009. “The Varying Impacts of Agricultural Support Programs on U.S. Farm Household Consumption”. American Journal of Agricultural Economics, 91(3):569–580.

CHAPTER 3. CONSUMPTION RISK OF FARM HOUSEHOLDS

3.1 Introduction

Between 1996 and 2013 median between-year change in farm income was a whopping 160% of median farm income (Key et al., 2018). The high variability in farm incomes lead many to consider farming a risky activity, with much time and effort spent on researching and implementing expensive public policy aimed at reducing income variability. Empirically however, we do not see these variations in farm incomes manifesting into large fluctuations in consumption, which may imply that a farm household's well-being is not as negatively impacted by the variation in farm income as traditional non-consumption-based risk measures would lead one to believe. When using consumption as the measure of household utility the appropriate risk measure of an income stream is one which measures the impact that income volatility has on consumption volatility; the consumption beta as derived by Breeden (1979) is one such measure. In this study we examine the riskiness of farm and nonfarm incomes by estimating their consumption betas using data from the Kansas Farm Management Association on 436 family-owned farms from 2001 to 2018.

A number of previous studies on farm household consumption have consistently shown that the marginal propensity to consume farm incomes is very low, at about 2% (Carriker et al., 1993; Langemeier and Patrick, 1990; Whitaker, 2009). This low consumption of farm incomes at the margin combined with evidence that the farm household is not liquidity constrained and consumes as predicted by the life-cycle income hypothesis (Langemeier and Patrick, 1993) strongly supports the idea that farm household consumption is not significantly impacted by the magnitude of farm income volatility.

Borrowing and lending as well as investing and disinvesting allows the farm household to transition cash flows from one period to another, and it is this mechanism that enables the farm household to maintain a relatively smooth consumption pattern in spite of variances in realized incomes. The action of borrowing and lending prevents income volatility from translating into consumption volatility as long as the farm household is not credit constrained. If income volatility does not affect the farm household's consumption of goods and services, one could argue that income volatility has minimal effect on farm household well-being. Figure 3.1 shows the mean net farm income and consumption of a sample of Kansas farm households and illustrates the relative stability of consumption.

An important risk management tool commonly used by farm households is the manipulation of hours worked off-farm by the farm operator and their spouse (Mishra and Goodwin 1998; Key et al. 2006). Nonfarm labor is a significant portion of total income and has contributed to median farm household income exceeding that of nonfarm households since the late 1990's (Mishra and Chang 2012; Todd and Whitt 2019). As evidenced by nonfarm incomes being consumed at a significantly higher marginal rate than farm incomes (Carriker et al. 1993; Whitaker 2009), it appears that the manipulation of hours worked off-farm is an effective tool at smoothing farm household consumption, allowing the household to offset would-be low income and consumption years with increases in hours worked off the farm. We estimate the consumption beta of nonfarm incomes and contrast them to those of farm incomes.

We find that the consumption betas of farm income and nonfarm income are small, and that nonfarm labor incomes are a particularly low risk component of nonfarm income. Upon examining the consumption betas of individual farm households, we find that operator age, number of dependents, household net worth, value of production, and specialization in crops versus livestock, are important in explaining the consumption risk posed by farm income, nonfarm income, and nonfarm labor incomes. We find particularly robust evidence that farms specializing in crop production have nonfarm labor incomes with lower consumption risk.

3.2 Methodology

Because of the existence of heterogeneity in consumption patterns and the possibility that aggregation hides within-household variation, we believe it is undesirable to use aggregate consumption data. Just as it is incorrect to use aggregate or market portfolio data in the context of measuring the risk impact of adding an asset to a specific agent's portfolio, we believe it is incorrect to use aggregate consumption data when measuring the risk that farm and nonfarm incomes pose to that household's consumption. We utilize data on individual farm households to measure risk relative to those household's own consumption patterns. By estimating risk measures from the perspective of the individual that owns and operates that farm we are departing from previous studies which estimate risk measures that are directly relevant only to some representative agent.

To our knowledge, the estimation of individual consumption-based risk parameters has not been done before, and previous studies using a consumption-based risk parameter have utilized aggregated data. We believe that individual data is superior to aggregates within this context not only because of the relevancy of the risk measures which are obtained, but also because aggregation can obscure changes in consumption volatility. Gorbachev (2011) provides a simple but illustrative example of how aggregate consumption volatility can be decomposed into the mean household consumption variance plus the mean covariance of household consumption. Aggregate consumption volatility may appear to be constant in spite of changes in household level volatility because of changes in the covariance between households. Therefore, if the covariance between households is not constant over time, then aggregate volatility is not an accurate proxy for household level volatility. Figure 3.2 shows the average covariance between households' demeaned consumption growth for rolling 5-year periods. Similarly, Figure 3.3 shows the average variance.

In addition to the problem of aggregation, some work analyzing farm household consumption uses an imputed proxy for consumption - such as farm withdrawals (Lence, 2000). We use reported household consumption data rather than an accounting measure proxy which may be muddled by withdrawals for the purpose of reallocation, diversification, or other non-consumption uses.

The consumption beta, $\beta_{a,C} = \frac{cov(C,r_a)}{var(C)}$ where C is consumption growth and r_a is the return of asset a, is a valid risk metric in the case of additive time-separable utility (Breeden 1979). The consumption beta is intuitive. With decreasing marginal utility, an asset which is more likely to generate high returns when your consumption is high, is less desirable than an asset that is more likely to generate high returns when your consumption is low. If consuming the assets returns would increase the volatility of your consumption then it is risk increasing, and if consuming the assets returns would decrease the volatility of your consumption then it is risk reducing. Equivalently, the consumption beta can be thought of as a measure of the relative difficulty of creating a smooth consumption pattern from asset returns, where returns of an asset with a lower consumption beta could be consumed more readily, while those with a higher consumption beta would require the use of additional financial instruments to result in a smooth consumption flow.

In the consumption capital asset pricing model (C-CAPM) the risk premium of an asset is proportional to the consumption betas of the asset and the market portfolio:

$$\mu_a - rf = \frac{\beta_{a,C}}{\beta_{M,C}}(\mu_M - rf) \tag{3.1}$$

where μ_a is the risk premium of asset a, rf is the risk-free rate, and M is the market portfolio.

In the asset pricing literature, references to the "consumption beta" are often references to the quotient shown in equation 3.1, which simplifies to the ratio of the covariances, $\frac{cov(C,r_a)}{cov(C,r_M)}$. By normalizing consumption betas by that of the market portfolio, the practical usage of the beta becomes like that of the ubiquitous CAPM beta (Sharpe 1964), where the beta is simply a multiplier of the market risk premium. While rescaling or normalizing the consumption betas such that the consumption beta of the market portfolio is equal to 1 is useful in asset pricing contexts, or examining the relative riskiness assets, it eliminates useful information about the absolute magnitudes of risk. By estimating the consumption betas and not rescaling them we are able to examine the possibility that certain farm household characteristics might affect the magnitudes of the consumption betas even if the relative riskiness of different income sources is unchanged.

Not rescaling the consumption betas is also necessary when estimating risk parameters for individual households to insure the correct interpretation of those coefficients. There is a possibility of the correlation between market returns and consumption being negative while the correlation between the returns of another asset and consumption is positive. In such a case, the market portfolio would be risk reducing and the other asset risk increasing - but the usual interpretation of the rescaled consumption betas would lead one to conclude that the other asset is risk reducing. To further motivate this point, returns on equity of individual farms often have a negative covariance with stock market returns (Tauer 2002, Bigge and Langemeier 2004), and so it is reasonable that consumption may as well. Therefore, to know whether an individual asset is risk reducing or risk increasing to an individual household, we must analyze the consumption betas comprising the C-CAPM individually.

We estimate a single common consumption beta for farm incomes using the following equation:

$$\beta_F = \frac{cov(C_{it},r_{it})}{var(C_{it})} \tag{3.2}$$

where r_{it} is the return on equity of farm i in time t. We also estimate a single common consumption beta for nonfarm incomes using a similar equation:

$$\beta_{NF} = \frac{cov(C_{it},NF_{it})}{var(C_{it})} \tag{3.3}$$

where NF_{it} is the percentage change in nonfarm income of household i in year t. Finally, we estimate a single common consumption beta for a component of nonfarm income, off-farm labor income.

$$\beta_W = \frac{cov(C_{it}, W_{it})}{var(C_{it})} \tag{3.4}$$

where W_{it} is the growth in off-farm labor income of household i in year t. In addition to the common risk parameters for all households, we also estimate individual consumption betas for each household and income source.

As is common in the C-CAPM literature, we utilize (three) lagged values of the independent and dependent variables as instruments when estimating the consumption betas. We estimate a common risk parameter for the whole sample by pooling the time series of all farm households together and clustering standard errors by farm household. We also estimate unique consumption beta parameters for each individual farm household with at least 10 observations. We then test if various farm household characteristics such as operator age, number of household members, acreage, or net worth, have any significant impact on the consumption beta of farm income, nonfarm income, or nonfarm wage incomes, as shown below:

$$\beta_i = a + B\Psi_{\mathrm{i}} + e_i \tag{3.5}$$

where β_i the consumption beta of either farm income, nonfarm income, or nonfarm labor income of farm household i, B is a vector of regression coefficients, Ψ_{i} is a vector of characteristics for farm household i, and e is an error term.

The characteristics which we examine are operator age, number of dependents, household net worth, value of production, and the percentage of farm labor dedicated to crops versus livestock. Because our estimates of the consumption betas are time invariant, we must make the decision of either including repeat observations of the same beta for as many years as a given farm household was observed or eliminating much of the variability in the characteristics by using some average value. We first estimate Equation 3.5 using the full sample of observations, where if a farm is observed 10 times, then their unconditional beta will be included in the regression 10 times along with 10 different observations of their characteristics. As a test of robustness, we then estimate Equation 3.5 using only one observation for each farm, using each farms characteristics mean values.

We use data from the Kansas Farm Management Association spanning the 2001 to 2018 period to conduct our analysis, and use real values calculated with the 2018 GDP price deflator. Data from the 2001 year is only used to calculate the growth in consumption, leaving 16 years of observations. While there are several thousand farms observed over the study period, but we only include a farm in the analysis if it has at least 10 observations. After accounting for missingness, there are 675 farm households that are included in the analysis.

3.3 Results and Analysis

Common consumption betas for farm income, nonfarm income, and off-farm labor incomes are reported in Table 3.1. All three of the consumption betas are economically small and are statistically indistinguishable from zero. It is possible that there is simply too much noise in the pooled household level data to reliably estimate the risk measure, these results are also precisely what one would expect if farm households were exhibiting perfect consumption smoothing. If consumption growth were constant, it does not matter what random vector one regresses against it, the parameter would always be statistically insignificant because it is in fact zero and both vectors are independent. Therefore, it may very well be correct that the risk parameters for farm incomes, nonfarm incomes, and off-farm labor incomes, are correctly estimated to be insignificantly different from zero, that incomes and consumption appear to be statistically independent, which would imply that incomes of farm households do not pose significant consumption risk.

The consumption betas of individual farm households reveal a clear pattern, as seen in Table 3.2. It appears that on average farm incomes are less risky that nonfarm incomes, but the consumption betas of nonfarm incomes have considerably more variation than the consumption betas of farm incomes. While on average nonfarm incomes are riskier than farm incomes, the left tail of the distribution shows that for a considerable number of households nonfarm incomes are risk reducing. Off-farm labor incomes appear to be risk reducing on average, and are likely one of the least risky components of nonfarm income.

The results of regressing our five farm household characteristics of interest onto the consumption betas of three income sources are reported with heteroskedasticity consistent standard errors in Table 3.3. The number of observations and households included in the model vary depending on the income source and is due to the removal of infinite values as well as missingness.

If a household increased their nonfarm income or off-farm labor income from zero to some positive value, then the percentage change would be infinite, and so those observations are removed from the sample.

The percentage of farm labor dedicated to crops as opposed to livestock is associated with an increase in the consumption risk of farm income and decreases in the consumption risk of nonfarm income as well as off-farm labor income. The relative labor intensity of livestock farming might explain these results. Livestock require daily care and may have life-threatening emergencies that are difficult to schedule around, crops don't. It may be easier for a crop farmer to adjust their off-farm labor hours to generate cashflow for consumption smoothing purposes than a livestock farmer, resulting in the negative association with consumption risk in nonfarm sources, while the positive association with consumption risk of farm income being the price paid for that off-farm labor flexibility.

Age is associated with a statistically significant decrease in the consumption risk of farm income, but no such significant effect on nonfarm incomes. A possible explanation for this might be that farmers become more risk averse with age and adjust their production practices accordingly.

Value of production is associated with a statistically significant increase in the consumption risk of farm income. A possible explanation might be that higher risk tolerances are associated with operating larger farms.

Net worth is associated with statistically significant increases in the consumption risk of farm income as well as nonfarm income, but no statistically significant effect on off-farm labor incomes. This result might be surprising, one might expect that as the wealth of the household increases, they become better able to smooth their consumption, resulting in smaller consumption betas. However, wealthier households can also afford to accept more risk from their income sources, as any shortfalls could be smoothed with savings. We believe that the increased risk tolerances may be dominating any reduction in consumption volatility, manifesting in wealth's positive association with the consumption risk of farm and nonfarm incomes.

Of the three income sources, variations in the consumption betas of nonfarm incomes are best explained by our five characteristics of interest. One way of ensuring that the statistical significance of certain variables are not overstated is to replicate the analysis with only one observation per farm household by using mean values. It very well could be that using mean values is the sounder approach, but it may also result in the elimination of important information. Consider the crop labor percentage. If a farm switches from exclusively crops to exclusively livestock over the sample period, the mean value would imply that the farm had a more diversified operation than they did. Using means also results in farm households which are observed 20 times over the sample period to be weighted the same as one who was only observed 10 times. Because of this, we believe that the results of using means in the regression analysis may be an extreme test of a robustness which could result in the failure to reject incorrect null hypotheses. The results of using only one observation per farm household is reported in Table 3.4.

At the 90% confidence interval the only statistically significant coefficient is the effect of the mean crop labor percentage on the consumption beta of off-farm labor income. Again, we find that specializing in crop production over livestock production is associated with off-farm labor incomes which are less risky.

3.4 Conclusions

While farm incomes are highly variable that uncertainty does not necessarily translate into risk from the perspective of the farm household. The ability of the farm household to borrow and lend, and invest and disinvest from the farm enterprise, allows the farm household the ability to effectively smooth their consumption. If the farm is not unable to borrow, or unable to forgo the replacement of farm assets, or is otherwise liquidity constrained, then uncertainty in incomes does not necessarily represent a risk to the household’s consumption and welfare. In effect, borrowing and lending acts as a buffer mechanism which prevents uncertainty from turning into risk, as long as the household does not become liquidity constrained.

Given that individuals derive utility from the consumption of goods and services and not simply by earning income, a correct risk measure is one which captures the relationship between income volatility and consumption volatility, such as the consumption beta (Breeden, 1979). We have estimated the appropriate parameters that represent the risk of farm and nonfarm incomes to the consumption of that same farm household.

Our estimates show that the volatility of farm and nonfarm incomes are not highly correlated with the fluctuations in consumption, and therefore pose no more risk to the household’s consumption problem than any other random income stream. We find evidence that off-farm labor incomes may be risk reducing for a large portion of farm households. This risk reduction effect could be due to the farm household manipulating the number of hours worked off-farm to prevent would-be shortfalls in consumption. Our findings add to the body of evidence showing that off-farm income is a powerful risk management tool and an important component of the farm households' total income. Our findings combined with the existing literature on the consumption of fluctuations in income show that the welfare of the farm household is not significantly affected by farm income volatility and at the same time may be greatly benefited by the ability to flexibly earn off-farm income.

After examining the individual consumption betas of many farm households, we find evidence that crop and livestock specialization, number of dependents, age, value of production, and net worth, are important variables in explaining the riskiness of incomes. Larger, wealthier farms have riskier incomes which covary more with consumption, with a plausible explanation being an increased risk tolerance due to the ability to better withstand fluctuations in income. A larger number of dependents is associated with less risky farm and nonfarm incomes, which might be explained by behavioral factors and lower risk tolerances. Specializing in crop production over livestock production is associated with more risky farm incomes but significantly less risk nonfarm incomes. Crop production may be easier to schedule around nonfarm employment opportunities than livestock, and that flexibility may better allow the farm household to alter their off-farm labor hours in response to potential decreases in consumption. This finding that crop production reduces the riskiness of off-farm labor incomes is particularly robust and large in magnitude.

Viewing farm risk as a consumption problem rather than an income variability problem we can come to policy suggestions that are quite different than those that are currently in place. Instead of reducing the variance of farm incomes with costly crop and revenue insurance or other counter-cyclical payments to fill in the income troughs of bad, one may be able to better the welfare of the farmer more cost effectively, and without raising the mean of farm incomes, by improving the accessibility of credit. By improving the ability of the farmer to borrow, the farmer would be better able to smooth their consumption, thereby reducing the risk that income variability poses to their welfare. However, our results, and prior studies on the liquidity of farm households, indicate that such an intervention may not be needed.

Table 3.1: Consumption Betas of All Households

	Farm Income	Nonfarm Income	Nonfarm Labor Income
Beta	-0.008	-0.005	-0.034
	(0.015)	(0.053)	(0.098)
Constant	-0.317	-2.410**	15.438***
	(0.425)	(0.928)	(1.713)
Observations	5,688	2,831	4,507
R-squared	0.00	0.00	0.00

*Standard errors in parentheses *p<0.10 **p<0.05 ***p<0.01*

Table 3.2: Selected Summary Statistics of Individual Consumption Betas

	1st Quartile	Median	Mean	3rd Quartile
Farm Income	-0.0419	0.0051	0.0391	0.0679
Nonfarm Income	-0.3619	0.0312	0.2240	0.4784
Off-farm Labor Income	-0.2207	-0.0122	-0.0061	0.2227

*Standard errors in parentheses *p<0.10 **p<0.05 ***p<0.01*

Table 3.3: Regression Analysis of Individual Consumption Betas

	Farm Income	Nonfarm Income	Off-farm Labor Income
Crop Labor Percentage	0.0395* (0.0205)	-0.2825*** (0.0950)	-0.1624*** (0.0352)
Dependents	-0.0424*** (0.0121)	-0.0407* (0.0227)	-0.0382*** (0.0075)
Age	-0.0047*** (0.0014)	-0.0031 (0.0042)	0.0005 (0.0009)
Value of Production ($1,000,000)	0.0270** (0.0121)	0.0597 (0.2842)	-0.0108 (0.0239)
Net Worth ($1,000,000)	0.0059* (0.0031)	0.4219*** (0.1425)	-0.0069 (0.0077)
Intercept	0.3827*** (0.1076)	0.0406 (0.2378)	0.2248 (0.0715)
Adj. R-squared	0.011	0.082	0.011
Observations	8,582	6,902	4,133
Farm Households	675	527	308

*Standard errors in parentheses *p<0.10 **p<0.05 ***p<0.01*

Table 3.4: Regression Analysis of Individual Consumption Betas - Means

	Farm Income	Nonfarm Income	Off-farm Labor Income
Mean Crop Labor Percentage	0.0909 (0.1249)	-0.1322 (0.3219)	-0.3328* (0.1680)
Mean Dependents	-0.8749 (0.0732)	-0.0997 (0.0784)	-0.0469 (0.0311)
Mean Age	-0.0091 (0.0077)	-0.0067 (0.0147)	0.0006 (0.0038)
Mean Value of Production ($1,000,000)	0.0758 (0.0799)	0.0328 (0.0970)	-0.0977 (0.1253)
Mean Net Worth ($1,000,000)	0.0183 (0.0210)	0.0597 (0.0651)	0.0490 (0.0402)
Intercept	0.7223 (0.5835)	0.2079 (0.6660)	0.3632 (0.2883)
Adj. R-squared	0.018	0.091	0.003
Observations	675	527	308
Farm Households	675	527	308

*Standard errors in parentheses *p<0.10 **p<0.05 ***p<0.01*

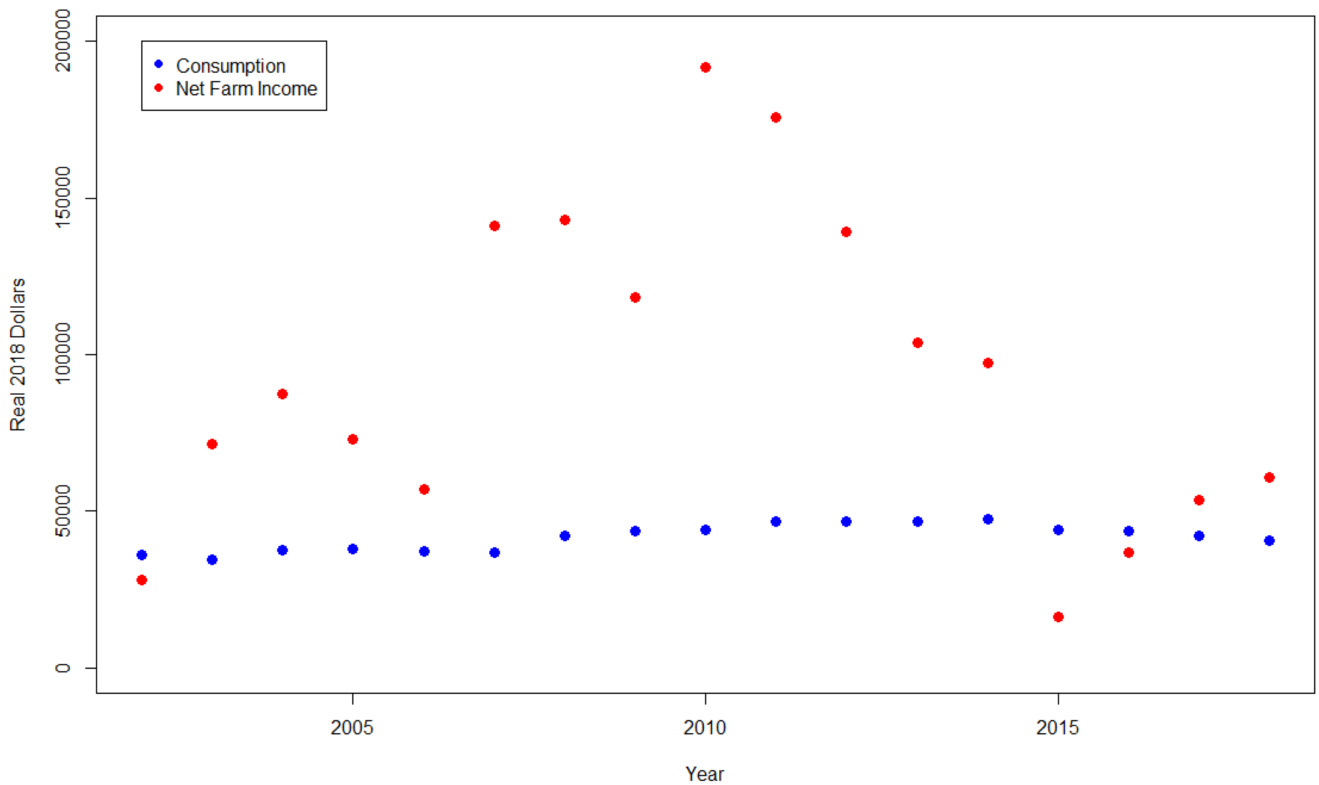

Figure 3.1: Mean Net Farm Income and Consumption

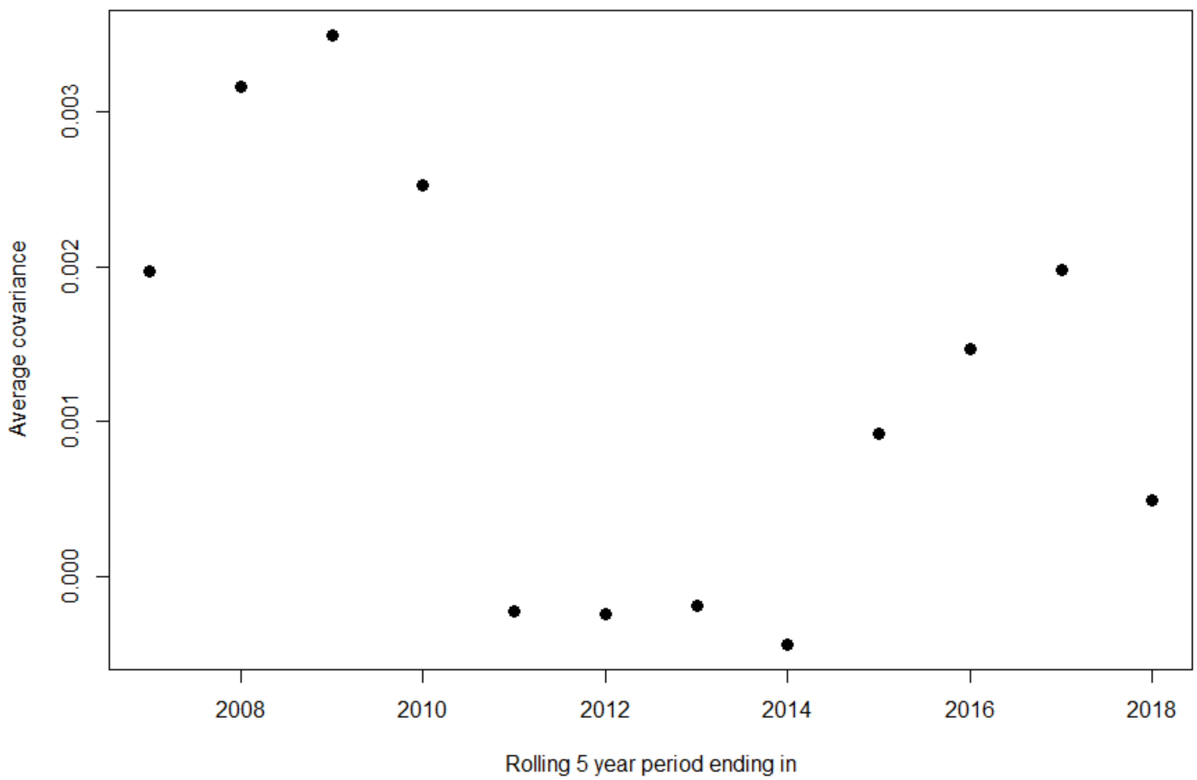

Figure 3.2: Average Covariance of Household Consumption

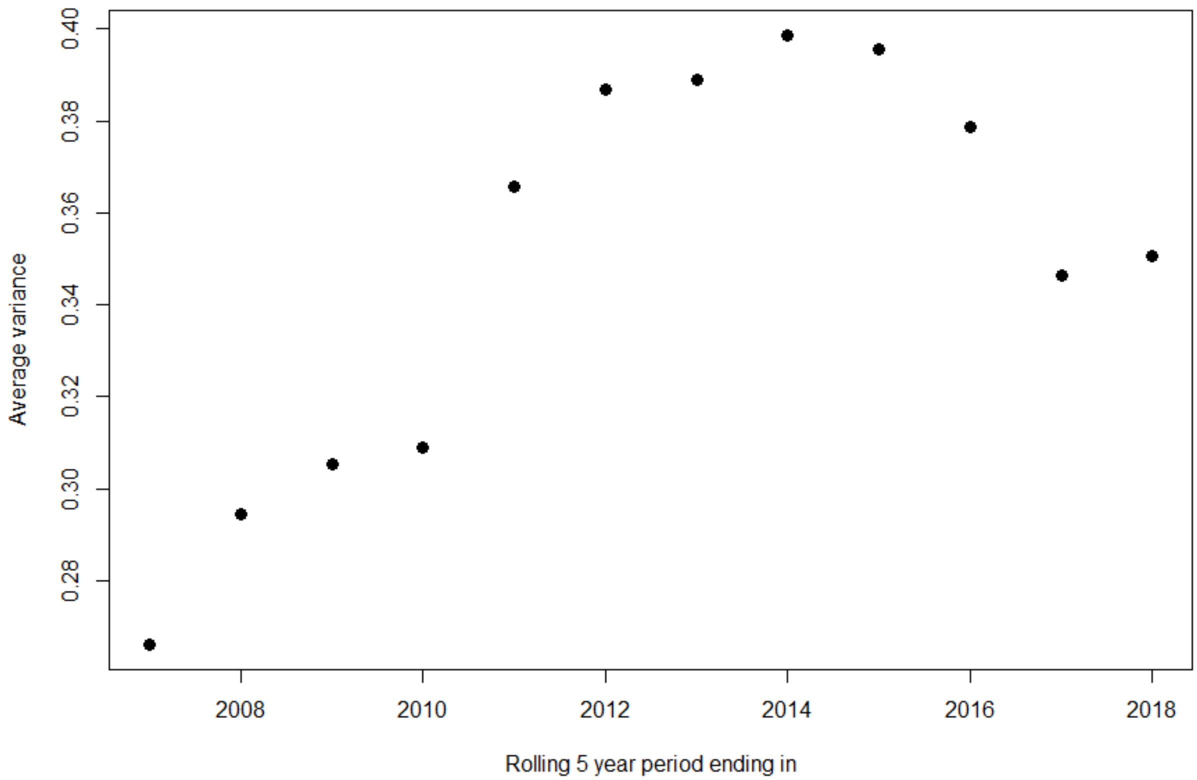

Figure 3.3: Average Variance of Household Consumption

3.5 References

Bigge, H. M., and M. R. Langemeier. (2004) Relative Profitability and Risk of Kansas Farms and S&P; 500. *Journal of the American Society of Farm Managers and Rural Appraisers*, no. 387-2016-22910 (2004): 57-63.

Breeden, D. T. (1979, July). AN INTERTEMPORAL ASSET PRICING MODEL WITH STOCHASTIC CONSUMPTION AND INVESTMENT OPPORTUNITIES.

Carriker, G. L., M. R. Langemeier, T. C. Schroeder, and A. M. Featherstone (1993, August). Propensity to Consume Farm Family Disposable Income from Separate Sources. *American Journal of Agricultural Economics 75*(3), 739.

Gorbachev, Olga. (2011). Did Household Consumption Become More Volatile? *American Economic Review* 101 (5): 2248–70. https://doi.org/10.1257/aer.101.5.2248.

Key, N., D. L. Prager, and C. B. Burns. 2018. The Income Volatility of U.S. Commercial Farm Households. *Applied Economic Perspectives and Policy 40*(2), 215–239.

Key, Nigel, Michael J. Roberts, and Erik O'Donoghue. 2006. Risk and Farm Operator Labour Supply. *Applied Economics 38*(5): 573–86. https://doi.org/10.1080/00036840500369043.

Langemeier, M. R. and G. F. Patrick (1990, May). Farmers' Marginal Propensity to Consume: An Application to Illinois Grain Farms. *American Journal of Agricultural Economics 72*(2), 309.

Langemeier, M. R. and G. F. Patrick (1993, May). Farm Consumption and Liquidity Constraints. *American Journal of Agricultural Economics 75*(2), 479.

Lence, S. H. (2000, November). Using Consumption and Asset Return Data to Estimate Farmers' Time Preferences and Risk Attitudes. *American Journal of Agricultural Economics 82*(4), 934–947.

Mishra, A. K. and H.-H. Chang (2012, February). Can off farm employment affect the privatization of social safety net? The case of self-employed farm households. *Food Policy 37*(1), 94–101.

Mishra, A. K. and B. K. Goodwin (1998). Income risk and allocation of labour time: an empirical investigation. *Applied Economics 30*(12), 1549–1555.

Sharpe, William F. (1964) CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK. *The Journal of Finance* 19 (3): 425–42. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x.

Tauer, L. (2002) "Estimating risk-adjusted interest rates for dairy farms." *Agricultural Finance Review*.

Todd and Whitt (2019, November). Income and wealth in context. https://www.ers.usda.gov/topics/farmeconomy/farm-household-well-being/income-and-wealth-in-context. Accessed: 2020-07-01.

Whitaker, J. B. (2009, August). The Varying Impacts of Agricultural Support Programs on U.S. Farm Household Consumption. *American Journal of Agricultural Economics 91*(3), 569–580.