2015

Determinants of Demand for Cable TV Services in the Era of Internet Communication Technologies

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December 17, 2015

Acknowledgements

Here I'd like to make some acknowledgements. Firstly, thank you Professor Shostya for you guidance and patience. Without your critique and faith in me it would be difficult for me to succeed. Thank you for having faith in me and letting me present while you still had your doubts. I'd like to thank Professor Weinstock for agreeing to be my second reader, providing me with powerful critique and questioning during my presentation, and expressing his pride in me after it was all said and done. Next, I'd like to say thanks and make my acknowledgements to Pamela, the Honors College's Senior Academic Advisor, for fighting to allot me more time to finish my thesis after I failed the first time - I'm grateful that you've been such a positive influence on me and believed in me. Finally, I'd like to thank the Honors College for taking me into its program, and my fellow peers and Honor students for being supportive and uplifting me in my times of darkness. Thank you all who supported me along the way!

Abstract

The rise of the Internet Communication Technologies (ICTs), such as video-on-demand (VOD) services, is expected to have substantial impact on the entertainment industry. In particular, cable TV is likely to be one of the media channels most affected by the expansion and development of these new technologies. Given these changes and the fact that the signs of the cable TV viewership decline are starting to show, it is important to investigate the potential of the loss of competitive advantage of television programming services.

Most of the existing research on the topic focuses on the relationship between TV viewing and Internet penetration. However, economic evidence on the relationship between cable TV services and such ICTs as VOD services is limited. In this paper, we empirically investigate the determinants of the demand for cable TV services in the era of ICTs. Our main objective is to identify the relationship between cable TV and VOD substitute services at the aggregate national level as well as identify some of the mechanisms behind this relationship.

We conduct an observational study using a sample of the U.S. quarterly national-level data for years 2008-2015. The data on the number of Time Warner Cable (TWC) subscribers is used as a proxy for cable TV consumption, while the data on the number of Netflix subscribers is used as a proxy for VOD services

consumption. We estimate several specifications of the OLS regressions controlling for own price, availability of related goods (VOD services, mobile phones, Internet), and income.

Our results contribute to the existing literature on the economics of entertainment by presenting evidence of substitution between the VOD services and cable TV services. More specifically, our estimates for the elasticity between TV and VOD services, obtained using first-differences OLS estimation, suggest that a 1 percent increase in the number of Netflix subscribers is associated with a 0.123 percent decrease in the number of TWC subscribers. This implies that providers are likely to benefit from focusing on offering extra value to consumers rather than trying to gain additional revenue through advertising. The results of the analysis also highlight that higher prices for cable TV services are likely to be interpreted by consumers as a signal for quality. More specifically, our estimates suggest that a 1 percent increase in own price is associated with 0.38 percent increase in the number of TWC subscribers. This implies that offering greater choice of programs and higher subscription prices might be the pricing strategy to increase revenues.

These findings provide a better understanding of the mechanisms behind consumer choice and decision-making processes. In turn, this understanding elicits valuable insights into television programming services revenue sustainability, and the competition of the providers of these services with the providers of the VOD services.

Table of Contents

List of Tables

INTRODUCTION

Television has become the dominant mass media channel in the United States since its introduction in the 1950s. The most recent estimates indicate that on average individuals in the U.S. devote more time daily to watching TV (more than 5 hours) than to any other leisure activity[Nielsen (2014); BLS (2014)]. Although its popularity among consumers has been persistent over the years, the signs of viewership decline are starting to show, especially among the younger population [Nielsen (2014); Liebowitz and Zentner (2012)]. This tendency is largely attributed to the increased competition from alternative offerings brought about by new technologies. More specifically, the evolving broadband infrastructure and the introduction of the Internet Communication Technologies (ICTs), such as video-on-demand (VOD) services, has created a disruption in the industry context [Liebowitz and Zentner (2015); Zentner (2008); Liebowitz (2006); Waldfogel (2010); Tryon (2013)]. The emergence of companies such as Netflix, Hulu, and Amazon Instant Video offers consumers greater degree of choice by increasing the variety of content that is available. Moreover, consumers also get to choose how to view the content given the increasing variety and portability of video players (e.g. smartphones, tablets, laptops). These changes have not only ensured the growing success of online streaming services, but also contributed to the loss of competitive advantage of television programming services[Reis (2015)]. Given the aforementioned changes, and the fact that television plays a key role in the media industry, it is important to look at the empirical economic evidence regarding the possible disruptions in the cable TV business models that stem from the introduction of the ICTs. The purpose of this study is to investigate the current determinants of the demand for cable TV services, specifically focusing on the role of the VOD services.

Unlike the majority of research conducted on individual level data, this analysis uses recent quarterly time-series data for years 2008-2015 to examine various aggregate-level factors such as the video-on-demand substitutes, and other consumption characteristics of the population.

Economic evidence on this topic has been sparse and largely conceptually indeterminate in nature. Given this gap in the academic literature, this study aims to contribute by identifying the potential of the VOD services to substitute cable TV services, and thus potentially disrupt the traditional cable TV business models that heavily rely on advertising and subscription fees to generate revenue.

We estimate several specifications of the OLS regressions controlling for own price, availability of related goods (VOD services, mobile phones, Internet), and income. The results of the analysis provide evidence of substitution between consumption of cable TV services for VOD services. More specifically, we measure the elasticity between Time Warner Cable (TWC) and Netflix use (proxies for cable TV services and VOD services respectively), and find a negative and statistically significant result – a 1 percent increase in the number of

Netflix subscribers is associated with a 0.123 percent decrease in the number of TWC subscribers.

These findings provide a better understanding of the mechanisms behind consumer choice and decision-making processes. In turn, this understanding elicits valuable insights into television programming services revenue sustainability, and the competition of the providers of these services with the providers of the VOD services.

The paper is organized as follows. Section 2 presents an overview of the relevant literature. The theoretical framework, the hypotheses tests, the data set, measures and variables are discussed in Section 3. In Section 4, I turn to the examination of the empirical strategy. Section 5 summarizes main results, after which section 6 discusses study limitations and policy implications. Conclusions are drawn in Section 7.

LITERATURE REVIEW

In general, to explain the demand for media services, researchers rely on standard microeconomic demand theory, in which the quantity demanded is a function of price, household income, various measures of “quality” of the service, availability of substitutes, and variables representing consumer tastes [Hothi and Bodkin (1980); Park (1972)]. The academic literature exploring the relationship between the introduction of the Internet Communication Technologies (ICT) and the associated changes in the demand for media services is dominated by the studies focusing on the music industry [Zentner (2006); Liebowitz (2008);Oberholzer‐Gee and Strumpf (2007); Reis (2015)]. The main reason behind the extensive research with this focus is the fact that over the last decade, the music industry has suffered substantial revenue losses due to Internet piracy. Overall, these studies present evidence of broadband penetration having large and negative effects on legal sales, and the number of physical music stores.

As Internet-based video distribution platforms began to emerge during the recent years, the topic of the current factors of demand for cable TV services has become increasingly prevalent in the media. Despite this, the amount of academic research focusing on how demand for cable TV services is affected by the introduction of ICTs is still relatively limited. The existing studies tend to focus on two channels through which ICTs are likely to affect TV viewing: (1) the impact of the increased programming variety caused by ICTs on the time spent viewing television programming; (2) substitution of the Internet as a form of entertainment that competes with the types of programming watched on TV.

For example, Waldfogel (2009) investigates whether web distribution stimulates or depresses television viewing. More specifically, the author uses survey data for television and web viewing gathered from a small group of U-Penn students between 2005 and 2007 to examine whether both unauthorized and authorized web video use (mostly via YouTube) displaces conventional television use. The results of the study provide evidence of both substitution and complementarity between TV viewing and web viewing. More specifically, the author presents evidence that conventional television viewing reduced by approximately 2 percent in the sample group, but was more than offset by increases in the overall viewing of the network-authorized programming. It is important to note that the results of this analysis should be interpreted with caution because of the limitations associated with the use of the survey data (mainly, it is not representative of the U.S. population).

A study by Liebowitz and Zentner (2012) employs observational panel data to examine the impact of broadband penetration on television programming viewing time. More specifically, the authors use data on TV viewing time in conjunction with data on Internet use, education, and income to measure the effects for various age categories of television viewers. Their main results indicate that the relationship between broadband penetration and TV viewing time differs for younger and older populations. The relationship is not statistically significant for individuals over 35 years old, but it is negative for younger individuals. The coefficients on income are positive and statistically significant, but very small in magnitude. At the same time, education is not associated with a statistically significant impact on viewership.

These latter findings are also consistent with the evidence found in the earlier studies [e.g.Comanor and Mitchell (1971); Park (1972);Hothi and Bodkin (1980); Good (1974); Panko, Edwards et al. (1975)]. More specifically, it has been shown that most socio-demographic characteristics are not statistically significant factors of the demand for pay TV services. Additionally, Kieschnick and McCullough (1998) present evidence that income is a non-significant factor of demand for cable TV. However, it is a more important determinant of the choice of the premium cable TV programming services. The results of this study also indicate that in the years before the introduction of ICTs, consumers used to subscribe to cable TV because of uniqueness and variety of the offered content.

Liebowitz and Zentner (2015) further explore the latter issue by examining the effect of the increased programming variety caused by the ICTs on the amount of time spent watching TV. To predict the effect, they use cable and satellite television's impact on viewing as a proxy for the likely future impact of the ICTs. The findings of the study suggest that the availability of the option of watching television online does not influence the amount of time an individual spends watching television in general, but merely shifts the consumption toward choices that are a better fit for individual consumer preferences. The result holds even for individuals who enjoy binge watching the shows; that is, the total amount of time spent watching TV tends to stay the same. This evidence supports the claim that cable TV services and online streaming services should be viewed as substitutes.

Reis (2015) takes a broader perspective and empirically examines the question of the substitutability between TV viewing and Internet use. The focus of the analysis is the relationship between TV and Internet use, and changes in this relationship associated with the increase in the number of channels offered on TV. The author uses both observational and experimental data to test two hypotheses at the household level: (1) whether TV and Internet are substitutes; (2) whether an increase in the number of quality channels available on TV impacts TV viewing time and Internet use. The results of the analysis provide evidence of substitution between TV and Internet use. More specifically, it is shown that an increase of 1 percent in average daily TV time is associated with a 1.55 percent decrease in the average daily download traffic. At the same time, a 1 percent increase in TV time is associated with a 0.25 percent decrease in download traffic.

A study by Chang, Kauffman et al. (2013)explores a different, but still relevant channel through which ICTs might be affecting TV viewing. The authors examine the switching patterns associated with the introduction of smartphones in Singapore in 2009. They hypothesize that the increased convenience of the access to digital content through smartphones results in the increased propensity to consume more media through them. More specifically, using Markov chain transition analysis, they evaluate the potential of this introduction to impact consumption of broadband Internet and cable TV. The presented evidence indicates the potentially strong negative relationship between the number of cable TV subscriptions and rollout of smartphone services.

This study is, to our knowledge, the first comprehensive analysis bringing together the findings of the previous research and identifying the mechanisms behind the demand for cable TV services and its determinants by using national-level aggregate data.

DATA AND MODEL

The classical demand theory and the results of the existing studies suggest that own price, availability of related goods (VOD services, mobile phones, Internet), and income are likely to be the key determinants of demand for cable TV services.

The data for the analysis was obtained from multiple sources listed in the Appendix A*[Table 1].* All data is publicly available, and there are no missing values. The analyzed dataset consists of national-level aggregate variables over 7-year period (2008-2015) divided in 29 quarters, and comprises 29 observations and 6 variables. The seven-year sample period from 2008 to 2015 was chosen for the empirical analysis based on the data availability and data quality. The records from the previous years either mostly private or come from printed sources that are not easily available and would require a substantial amount of time to process.

In the analysis we examine quarterly aggregate national-level data to empirically investigate the determinants of demand for cable TV services. More specifically, we use the data described above to build the following model:

$$twc_t = \beta_1 + \beta_2 ns_t + \beta_3 ip_t + \beta_4 mswvomp_t + \beta_5 wii_t + \beta_6 rdpi_t$$
$$+\beta_7 twctvgpp_t + \sum \beta d_{st} + \varepsilon_t$$

The variables in the model are in the natural logarithm form. This specification allows capturing the proportional percentage effect of changes in explanatory variables, and interpreting the coefficients as elasticities.

The dependent variable twc_t is the total number of Time Warner Cable subscribers in period *t*.

The independent variables of the regressions are defined as follows:

ns_t is defined as the natural logarithm of the number of Netflix subscribers in period t. This variable is used as a proxy for consumption of the VOD services in general.

ip_t is the Internet penetration rate in period t. This variable is included because the use of the Internet is expected to alter the time spent on more cable TV related entertainment. Consumption of new entertainment activities, such as using VOD services or online game playing, is directly related to the Internet penetration rate.

$mvswvomp_t$ is the number of mobile video subscribers watching video on a mobile phone. This variable is included because mobile videos are another important source of entertainment (especially for younger population) that might reduce television viewing. Conversely, they might also increase television viewing when they are used to watch television.

wwi_t is the number of the Wii console sales. This variable is included because Wii consoles: 1) offer access to VOD services; 2) might serve as a substitute to television viewing themselves. We expect to see a negative sign on this coefficient.

$rdpi_t$ is defined as real disposable income. The ability to purchase a cable TV subscription is related to the ability to purchase a television, the quality and size of the purchased television etc. Income is likely to influence the dependent variable because cable TV might be considered to be a normal good. This implies that as income rises, it is expected that the quantity demanded for cable TV services will increase, holding everything else constant. However, income could also be related to the opportunity cost of time spent watching television and the ability to participate in other forms of substitute entertainment activities.

twcptvpp$_t$ is the price of the TWC preferred TV package. This is the only variable that required our own calculation. We used the data on the current price level and the information that it has been going up by approximately 6 percent on average annually, to calculate the price levels using the net present value formula. Following standard demand theory, we anticipate a negative sign for the coefficient of this variable.

$\sum \beta d_{st}$ is a set of quarterly dummy variables d_{st} that are introduced for each quarter between 2008 and 2015 with the Q4 as the omitted category. These dummy variables take a value of 1 for their respective quarter and 0 otherwise. The fourth quarter is left out, so the coefficients measure the difference between each of the other quarters and the fourth quarter. Including time dummy variables in the model also helps to account for the effect of inflation.

ε_t is the error term of the model capturing the effects of the omitted variables.

Descriptive statistics for all the variables is presented in Table 2 (Appendix A). It presents preliminary evidence that confirms the hypotheses discussed above. For example, the average number of TWC subscribers decreased over time, while the Internet penetration rate, the number of Netflix subscribes, Wii sales, and the number of mobile video subscribers increased.

EMPIRICAL ANALYSIS

The Stata output for the empirical analysis is presented in the Appendix B. Initially, we use the Ordinary Least Squares (OLS) method to estimate the model. The dataset consists of 29 observations for the time period from Q1 2008 to Q1 2015. The first regression results are presented in Column 1 of Table 3. They indicate that *ns, mvswvomp, rdpi,* and *twcptvpp* are statistically significant variables at the 95% level of confidence. To examine the model, we consider the main OLS violations such as model misspecification, influential outliers, multicollinearity, autocorrelation and heteroskedasticity.

We start by checking for the model misspecification. Misspecification of econometric models is associated with biased coefficients and error terms, which in turn might result in incorrect inference. We use the Ramsey RESET general specification test to see if the model is specified correctly. The logic behind the test is that if non-linear combinations of the explanatory variables have any power in explaining the response variable, the model is misspecified. We use the F-statistic to test the null hypothesis that there is no model misspecification, and find that the model is specified correctly(the value is significantly greater than 0.05). To double-check the results, we then perform *linktest*. This test is based on the idea that if a regression is properly specified, one should not be able to find any additional independent variables that are significant except by chance. The Stata command creates the variable of prediction and the variable of squared prediction and refits the model using these variables as predictors. By looking at the p-value for the coefficient on the variable of squared prediction, we find that the coefficient is not statistically significant. This result indicates that the model is specified correctly.

Checking for influential outliers is another important step in empirical analysis. It is essential to perform this check because a single observation significantly different from the other observations may be indicative of the poor quality of the data and might be driving the results of the regression analysis. To detect potential outliers, first, we perform a graphical check. This is done by plotting the dependent variable against the independent variables and visually checking for the presence of outliers (Figures 1-6). These plots do not show the existence of severe outliers. The only possible exception is the real disposable income level in the year 2012.

To account for the fact that the presence of the outliers might depend on how many explanatory variables are taken into account at this stage of analysis, we build a scatter plot of squared residuals (Figure 7) and variable plots for all the variables (Figure 8). This provides a better visual check for the outliers. A scatter plot of squared residuals indicates that 2011Q3, 2011Q4, 2013Q3, 2013Q4 deviate from a pattern of residuals. Added variable plots indicate that 2012Q1, 2013Q1, 2013Q4 might be driving the results of the analysis. However, it is important not to put too much weight on these results before checking for numerical measures and to interpret them carefully given the small size of the analyzed dataset.

We then compute numerical measures detecting potential outliers. More specifically, we use studentized residual, leverage and DFfits. By examininig studentized residuals with a stem and leaf plot and showing the 10 largest and 10 smallest residuals, we find two observations (2013Q3, 2013Q4) with absolute value exceeding 2 (critical value for the RStudent t-test). Next, we look at the leverages to identify observations that have potential influence on regression coefficient estimates. According to the results, no observations are influential (greater than 3k/n[1], where k=number of explanatory variables, n=number of observations). We also plot leverage against squared residuals (Figure 9) to graphically double-check our results, and find that 2011Q3, 2013Q4 appear to have the largest residual and the largest leverage. This finding is consistent with the results of the previous checks and implies these observations are potentially the most influential. We then turn to the overall measure of influence and perform DFfits. This measure summarizes the influence of observations on the overall fit of the model by examining the changes in the predicted values following the adding/deleting of individual observations. In our case, the results suggest 2013Q4 is the most influential observation.

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[1] Recommended for small sample sizes

All the aforementioned evidence suggests that 2011Q3 and 2013Q4 observations could be driving the results of the regression analysis. We exclude observations one by one and reiterate the analysis. The magnitude of the coefficients changes slightly, and the *wiiln* variable becomes statistically significant at the 95% level of confidence. After these exclusions, observations 2011Q4 and 2013Q3 appear to be driving the results. We exclude these observations and compare the results of the analysis to the initial analysis. Given that the model coefficients and prediction variance do not change significantly, it is reasonable to conclude that these outliers are not influential.

In the end, we decide not to exclude any observations for the following reasons: (1) examining the data and the historical context of the data does not seem to provide grounds to assign economic meaning to the aforementioned influential points;(2) given that the purpose of the model is mostly explanatory, rather than forecasting, deleting accurately recorded data is likely to be inappropriate; (3) the elimination of the observations would lead to the presence of the gaps in an otherwise smooth time series dataset.

Normality of residuals is another assumption that is necessary to assure the validity of the statistical inference. Therefore, we check for it by performing graphical analysis and running the Shapiro-Wilk W test for normality. In particular, we plot kernel density estimate plot (Figure 10) and compare it to the normal density. Then, using *pnorm* and *qnorm* commands in Stata, we look at a standardized normal probability plot sensitive to non-normality in the middle range of the data (Figure 11), and plot of the quantiles of r against the quantiles of normal distribution sensitive to non-normality near the tails (Figure 12). Graphical analysis indicates there is evidence of slight non-normality in the residuals. Having performed the Shapiro-Wilk W test, we confirm that residuals are not normally distributed (p-value greater than 0.05 indicates that wefail to reject the null hypothesis that residuals are normally distributed).

We further check for heteroskedasticity in the model. It might be present in the model due to the nature of the data – multiple observations across time. Thus, there might be serial correlation across residuals. To check for heteroskedasticity, we perform the White test and the Breusch-Pagan test. Both test the null hypothesis that the variance of the residuals is homogenous. Looking at the p-value for both the Breusch-Pagan test and the White test, we fail to reject the null hypothesis that the variance is homogenous. Because, both of these tests are sensitive to model assumptions (e.g. normality), we combine them with diagnostic plots to look at the possible presence of heteroskedasticity (fitted values versus residuals plot, Figure 13). The graphical analysis does not provide conclusive evidence of the presence of heteroskedasticity.

Another important concern in our model is multicollinearity. Testing the model for this problem is necessary because the estimated coefficients may become unstable along with the inflated standard errors as the degree of multicollinearity increases. Checking the model with the correlation matrix and variance inflation factor (*VIF)* provides evidence of serious multicollinearity. This is expected given the nature of the data (time series) - all independent variables might be following the same trend, and thus end up highly correlated. The first-difference transformation helps to minimize such dependence by removing the trend component of the time series. Therefore, we re-estimate the model with the transformed variables, and find no evidence of serious multicollinearity.

Autocorrelation is another important issue with any time series data. Ignoring the fact that variables might be trending over time could return misleading results, and lead to unbiased, but inefficient estimates. In our case, first-differencing the data performed in the previous step is expected to take care of this problem. To check for its presence we perform the Durbin-Watson test. Looking at the Durbin-Watson statistic, we conclude that: (1) there is no statistical evidence that the error terms are positively autocorrelated (For k=6, n=28; dl=0.764, du=1.729. dl<d=2.027>du); (2) there is no statistical evidence that the error terms are negatively autocorrelated (dl<4-d=1.973>du).

ESTIMATIONRESULTS

The OLS regression results estimated with the transformed first-differenced data are presented in Table 3 (Column 2). For the sake of comparison, the first column presents results estimated with the data in the natural logarithm form. The coefficients from column 1 are interpreted as elasticities. The coefficients from column 2 represent the first differences of the logs, and are interpreted as approximate percentage changes. It is important to note that estimates from Column 1 suffer from the multicollinearity problem, and therefore the validity of the statistical tests is highly questionable. Therefore, we will interpret only the first-differenced estimates. Seasonal dummy variables were dropped as regressors after we regressed them onto the dependent variable and found that they are not statistically significant (Table 4, Column 1).

Overall, the OLS coefficients give information on the effects of independent variables on the number of TWC subscribers. We find that the F-value is significant for the first-differenced model. Two out of six explanatory variables are statistically significant at the 95% level of confidence. These regressors are *ns* (the number of Netflix subscribers) and *twcptvpp* (the price of the TWC preferred TV package).

One of the main objectives of the analysis is to estimate elasticity between the number of TWC subscribers and the number of Netflix subscribers. The coefficient on the number of Netflix subscribers confirms the hypothesis that consumers tend to substitute cable TV consumption for VOD services. The coefficient is negative and statistically significant at the 95% level of confidence (p-value=0.038). More specifically, if the other factors included in the model remain the same, but the number of Netflix subscribers increases by 1 percent, the number of TWC subscribers is supposed to decrease by approximately 0.123 percent.

The coefficient on the price of the TWC preferred TV package is positive and statistically significant at the 95% level of confidence (p-value= 0.000). More specifically, it implies that, holding all else constant, a 1 percent increase in own price is associated with 0.38 percent increase in the number of TWC subscribers. This is an interesting result given that standard demand theory predicts the inverse relationship between own price and quantity demanded. Although we can provide some rationales, we do not claim to have a clear understanding of the sign reversal. One of the possible and most plausible reasons behind this finding is that price is very likely to be correlated with the unobserved factors that also influence the number of TWC subscribers. Unfortunately, given the limitations of our data, it is impossible to properly adjust the identification strategy in our analysis. Alternatively, the "price tag" of the TWC package might be interpreted by consumers as a signal for the quality of the product. Liebowitz and Zentner (2015) emphasize that subscription-based demand is related to the value that viewers place on the programs they watch. Therefore, if cable TV companies started offering greater choice of programs (and thus increased the value that consumers receive), higher subscription prices could result in higher willingness to pay for services and increasing revenues.

The remaining coefficients in the model are not statistically significant at the 90%, 95%, or 99% levels of confidence. For example, the coefficient on real disposable income is positive, which appears to confirm the hypothesis that cable TV is normal good (holding everything else constant, an increase in income is associated with an increase in the number of cable TV subscribers). However, it is not statistically significant (p-value=0.106). Although we cannot interpret these coefficients, it is important to note that they play an important role in the model because they allow us to demonstrate that demand for VOD services has a significant impact on the demand for cable TV services.

Given that consumption of new entertainment activities, such as using VOD services or online game playing, is directly related to the Internet penetration rate, we are also interested in isolating the effect of the Internet penetration on the number of TWC subscribers. For this reason, we estimate an alternative specification of the model presented in Column 2 of Table 4. The coefficient on ip_t is not statistically significant at the 95% level of confidence (p-value= 0.972).

LIMITATIONS AND STRATEGICIMPLICATIONS

In part, our results might be improved by the use of better, richer data and more sophisticated econometric techniques. First, given that the sample is representative of the U.S. population, the extent to which the findings can be generalized across different geographic regions certainly requires further investigation. Second, the analyzed dataset is constructed from various sources that employ different methods of collecting the data. This might be indicative of possible measurement errors. Third, the analyzed dataset is aggregated time-series. This implies that the variables are likely to be exhibiting trending behavior, and, as a result, suffer from multicollinearity and autocorrelation. Although first-differencing the data alleviates these problems, the use of disaggregated panel data (e.g. household data) can potentially improve the precision and efficiency of the results. It would also potentially allow to (1) control for the presence of confounding factors (e.g. like the ones affecting our coefficients on own price and demand simultaneously); (2) study the effects for different household characteristics (e.g. income level). Fourth, unfortunately, because the price of our proxy for VOD services (Netflix) has remained constant over time, we are unable to estimate cross-price elasticity of demand for cable TV services. Obtaining a richer dataset (e.g. data on prices and consumption of a different VOD service) would allow such estimation. Fifth, given the nature of our data, there is a potential that some important determinants of cable subscribership are omitted from the analysis (e.g. quality of services, household viewing preferences).

With these caveats in mind, business implications of our results for providers of cable TV services and VOD services can be suggested. The central tendency of our point estimates suggests that consumers tend to substitute cable TV consumption for VOD services. The competition between cable TV services providers and VOD services providers is expected to become increasingly fiercer given that in recent years features of the former have started to increasingly approximate those of the Internet (e.g. VOD services, time-shift consumption), and that Internet features have started to approximate those of TV (high quality and speed of streaming). The knowledge of the substitution rates between cable TV and VOD streaming services can provide useful insights for the business strategies of both sides. Given that the previous studies indicate that total viewing does not appear to increase as more choice is made available [Liebowitz and Zentner (2015)], it is reasonable to suggest that providers should be focusing on offering extra value to consumers through, for instance, additional choices or switching to the Internet, rather than trying to gain additional revenue through advertising targeted to increase quantity of viewing among the existing subscribers. Thus, the results of the analysis suggest profitable channels for the companies to invest their advertising money, and provide insights on the drivers of service adoption among consumers.

From the antitrust policy-makers standpoint, the results can be helpful in assessing market power and analyzing competitive effects of the potential mergers in the industry. Though still small, the VOD services niche of the TV industry is growing rapidly, and monitoring by the Federal Communications Commission (FCC) and antitrust authorities is becoming of increasing importance.

CONCLUSIONS

The rise of the Internet Communication Technologies (ICTs) is expected to have substantial impact on the entertainment industry, and cable TV in particular. Despite a lot of media attention, economic evidence on the relationship between cable TV services and ICTs is relatively limited. This study contributes to the existing literature by identifying the potential of the VOD services to substitute cable TV services. Our goal in this research is to empirically investigate the determinants of the demand for cable TV services in the era of ICTs. Our approach is to empirically test the relationship between cable TV and VOD substitute services at the aggregate national level as well as some of the mechanisms behind this relationship. We conduct an observational study using a sample of national quarterly data for years 2008-2015. Our estimates for the elasticity between TV and VOD services are obtained using OLS and suggest that a 1 percent increase in the number of Netflix subscribers is associated with a 0.123 percent decrease in the number of TWC subscribers. The results are consistent with the existing literature, and imply that substitution exists between consumption of cable TV services for VOD services, and that providers should be focusing on offering extra value to consumers rather than trying to gain additional revenue through advertising. It is important to note that all results must be interpreted carefully due to the potential data limitations discussed in the previous section.

Although, our findings provide a better understanding of the mechanisms behind consumer choice and the competition of the cable TV providers with the providers of the VOD services, there are a number of future additions that could be made to improve the effectiveness of this paper. First, there is a need to develop a statistical framework to make more precise causal inferences, which involves identifying appropriate counterfactuals and quasi-experimental variation. For example, we plan to develop a statistical model to validate the effect of VOD services on switching behavior. Instead of using aggregate time-series data, individual-level panel data could be used. This would allow capturing individual characteristics (such as age or geographic location) and adding levels of granularity to the analysis. It might be interesting to check the hypothesis that there is difference in the behavior of different demographic groups and link those to the individual segment responses rather than the population as a whole. Second, we believe more research is needed to assess the role of the increasing use of various portable devices on the relationship between cable TV and VOD services. The changes brought about by a shift to viewing over portable devices are likely to increase overall viewing. Exploring this topic is an interesting avenue for future research (we did not look into it because of the data limitations). Another promising extension for future research is focusing on service characteristics as a possible factor in consumer choice when it comes to cable TV and VOD services. Finally, the type of analysis we do here can be extended to study the outcomes for other VOD services. Although the eventual economic importance of the ICTs remains uncertain, given its recent rate of growth, the demand for economic studies to inform companies and public policy toward this industry is certain to rise.

APPENDIX A: Tables

Table 1: Measurements and sources of data

Variable	Description	Measurement	Source
twc	The number of TWC subscribers	Individuals, millions	TWC investor news and Securities and Exchange Commission (SEC) filings http://ir.timewarnercable.com/investor-relations/investor-news/default.aspx
ns	The number of Netflix subscribers	Individuals, millions	Netflix quarterly SEC filings http://ir.netflix.com/sec.cfm
ip	Internet penetration	Individuals, millions	Akamai*State of the Internet* reports https://www.stateoftheinternet.com/connectivity-akamai-cdn-state-of-the-internet-reports.html
mvswvomp	The number of mobile video subscribers watching video on a mobile phone	Individuals, millions	Nielsen *Total Audience* reports http://www.nielsen.com/us/en/insights/reports.html
wwi	The number of the Wii console sales	Individuals, millions	Video Game Charts (VGChartz) data http://www.vgchartz.com/weekly/42204/USA/
rdpi	Real disposable income	USD, quarterly	FRED® economic data, Federal Reserve Bank of St. Louis https://research.stlouisfed.org/fred2/series/DSPIC96
twcptvpp	The price of the TWC preferred TV package	USD, quarterly	TWC website http://www.timewarnercable.com/content/twc/en/plans-packages/tv/digital-cable-tv-plans.html/ Bloomberg News http://www.bloomberg.com/news/articles/2015-01-07/why-your-cable-bill-is-going-up-again-in-2015-sports

Table 2: Summary statistics

Year	TWC (in millions)		Netflix (in millions)		Internet Penetration Rate (in millions)		Income ($)		Mobile Video Watching (in millions)		Wii Sales (in millions)		TWC Price ($)		N
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
2008	13.2	0.11	8.68	0.51	106	7.67	10987.35	115.89	0.01	0.001	12.4	3.55	43.22	0	4
2009	13	0.11	11.1	0.86	119	4.35	10942.83	60.84	0.02	0.002	21.8	2.98	45.82	0	4
2010	12.6	0.24	16.4	2.43	135	5.38	11055.2	115.67	0.02	0.002	30.1	2.45	48.56	0	4
2011	12	0.14	23.9	8.06	144	1.34	11331.3	32.41	0.03	0.002	36.3	1.66	51.48	0	4
2012	12.2	0.18	29.1	3.11	145	1.81	11687.85	170.4	0.04	0.002	39.7	0.66	54.57	0	4
2013	11.6	0.32	39.6	3.56	156	7.11	11523.15	70.15	0.06	0.03	41.1	0.2	57.84	0	4
2014	10.9	0.17	52.2	3.96	157	4.61	11836.33	127.36	0.12	0.01	41.6	0.06	61.31	0	4
2015 Q1	10.8	-	62.3	-	152	-	12110.8	-	0.13	-	41.7	-	64.99	-	1
Overall	12.2	0.8	27.1	16.3	138	18.5	11364.37	372.2	0.05	0.04	32.2	10.6	52.28	6.51	29

Table 3. Regression Estimates

Variables	OLS1	OLS2 *(first differences)*
nsln	-0.17 ***	-0.12**
	(0.03)	(0.06)
ipln	0.1	0.05
	(0.08)	(0.08)
mvswvompln	-0.06***	-0.01
	(0.01)	(0.02)
wiiln	0.03*	0.01
	(0.02)	(0.03)
rdpiln	0.45*	0.28
	(0.20)	(0.16)
twcptvppln	0.48***	0.38***
	(0.11)	(0.09)
_cons	11.34***	-0.01
	(2.55)	(0.00)
R^2	0.98	0.49

* denotes statistical significance at the 90% level of confidence; ** at the 95% level of confidence; *** at the 99% level of confidence.

Table 4. ExploratorySpecifications

Variables	OLS3	OLS4 *(first differences)*
ipln		0.003
		(0.97)
twcptvppln		0.29*
		(0.004)
Q1	0.005	
	(0.89)	
Q2	-0.01	
	(0.81)	
Q3	-0.02	
	(0.52)	
_cons	16.32***	-0.01***
	(0.00)	(0.001)
R^2	0.03	0.30

* denotes statistical significance at the 90% level of confidence; ** at the 95% level of confidence; *** at the 99% level of confidence.

APPENDIX B: Stata output

Ramsey RESET test using powers of the fitted values of twcln

Ho: model has no omitted variables
F(3, 19) = 0.80
Prob> F = 0.5110

Linktest

Source	SS	df	MS	Number of obs =	29
				F(2, 26) =	753.27
Model	.123285586	2	.061642793	Prob> F =	0.0000
Residual	.002127685	26	.000081834	R-squared =	0.9830
				Adj R-squared =	0.9817
Total	.125413271	28	.004479045	Root MSE =	.00905

twcln	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_hat	7.430784	13.61485	0.55	0.590	-20.55493	35.4165
_hatsq	-.1972406	.4175845	-0.47	0.641	-1.055598	.6611167
_cons	-52.41606	110.9725	-0.47	0.641	-280.5234	175.6913

Figure 1. Scatterplot of twcvs ns

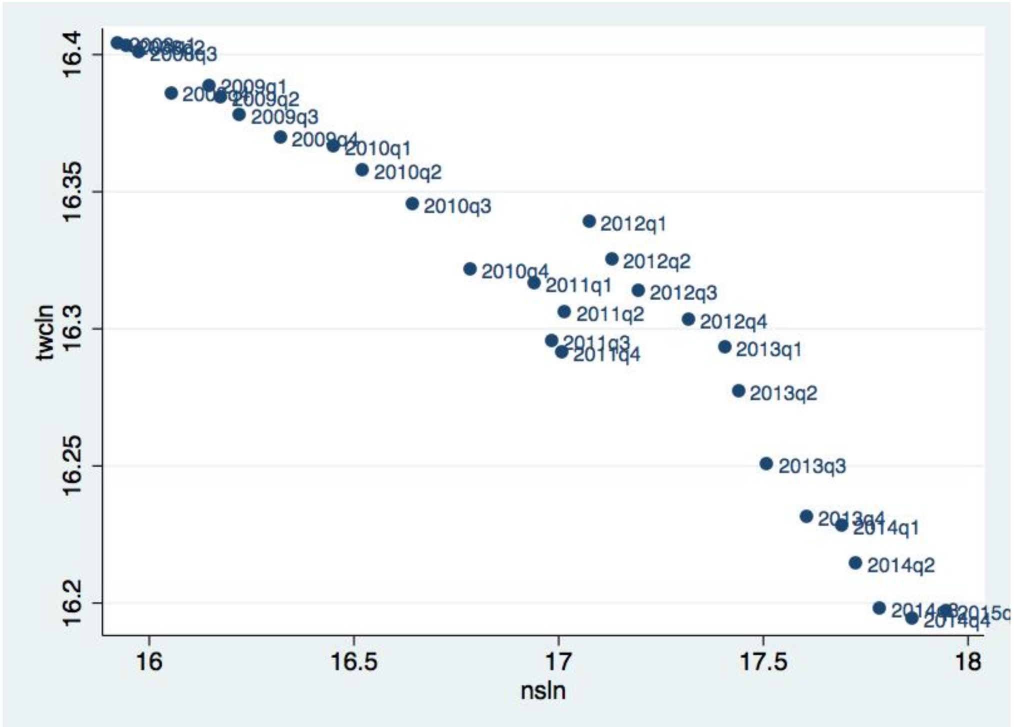


Figure 2. Scatterplot of twcvsip

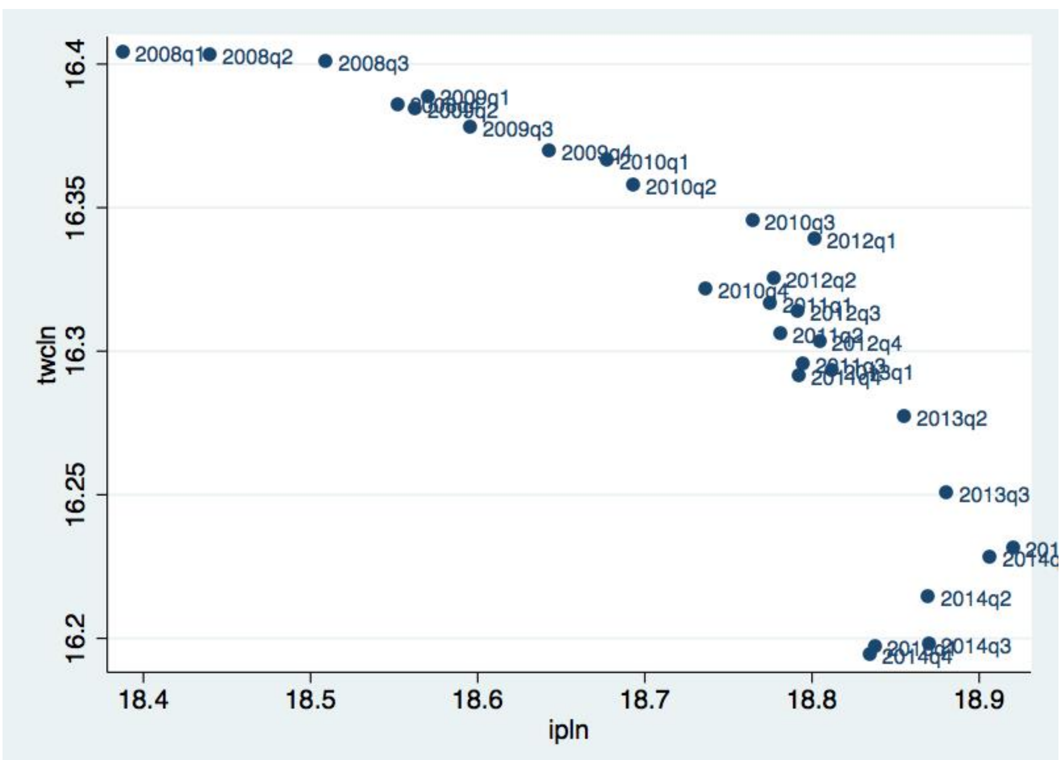


Figure 3. Scatterplot of twcvsmvswvomp

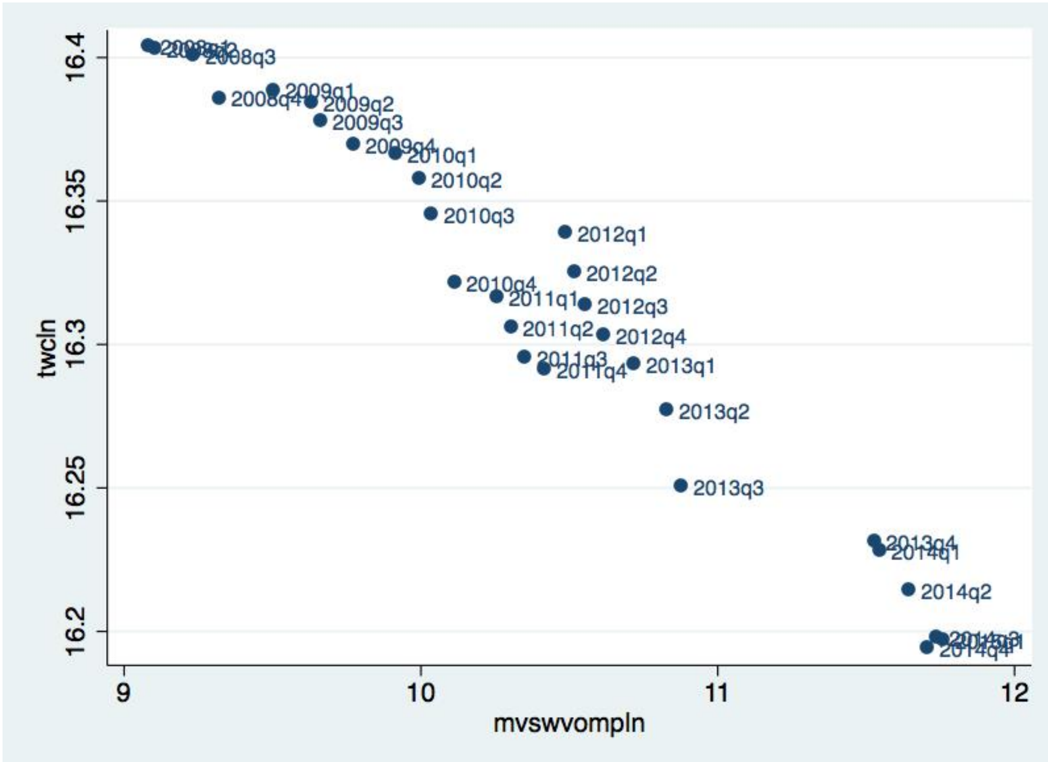


Figure 4. Scatterplot of twcvswii

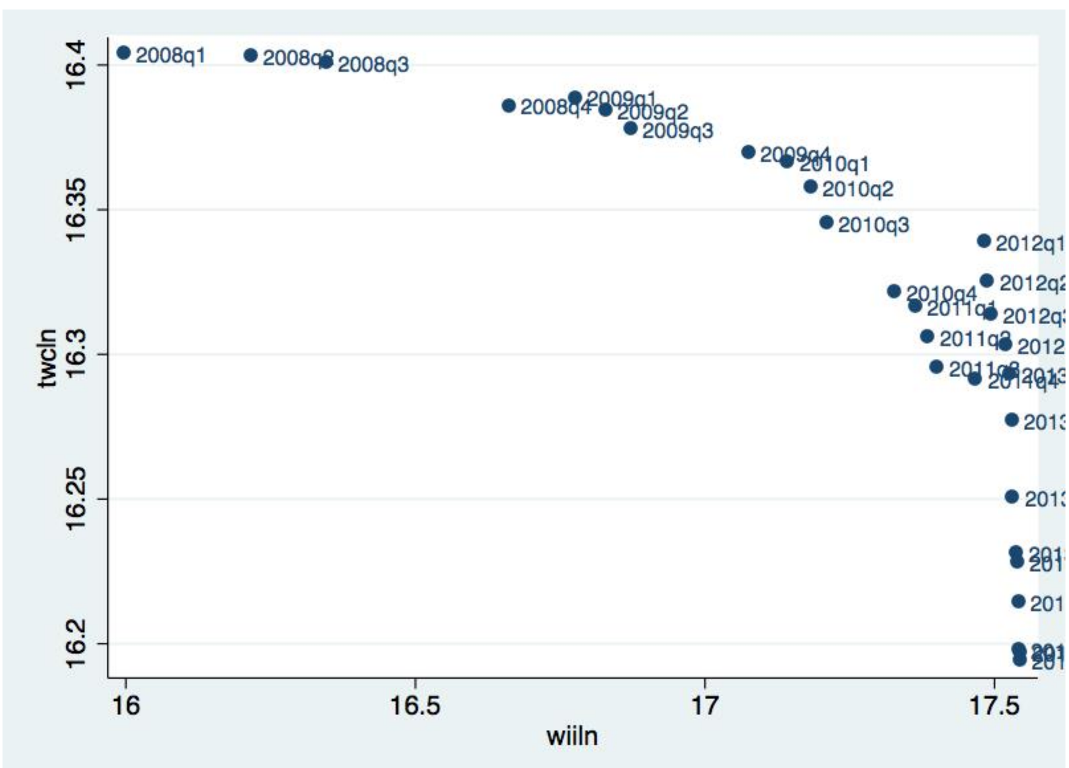


Figure 5. Scatterplot of twcvsrdpi

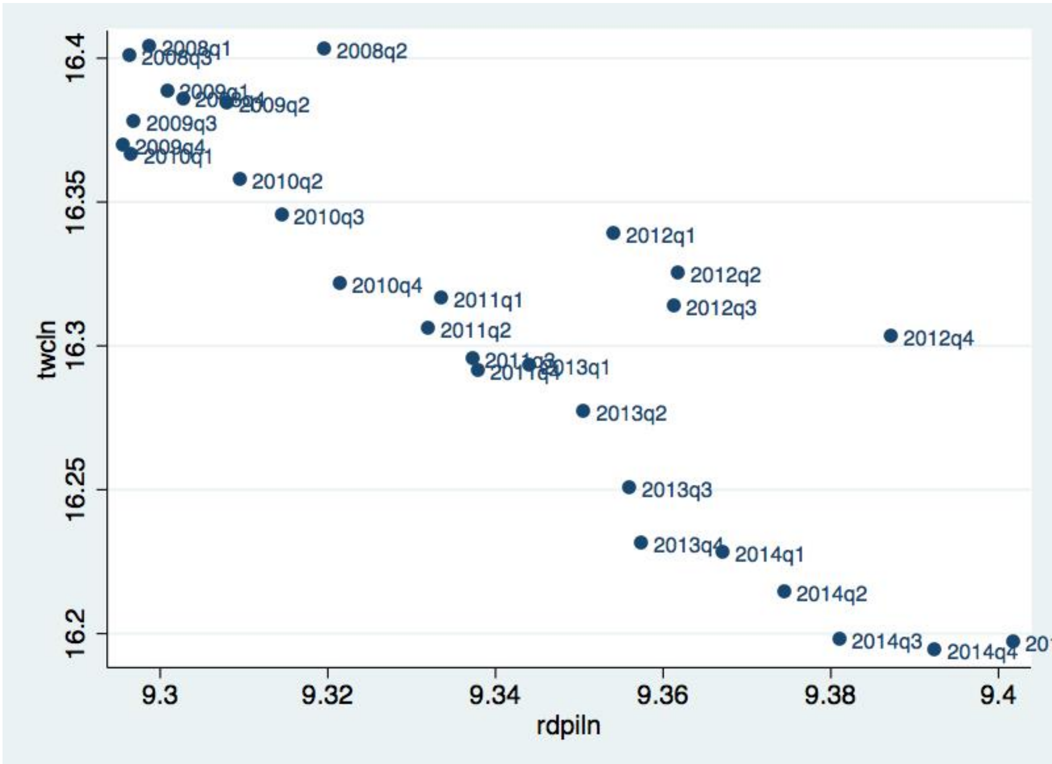
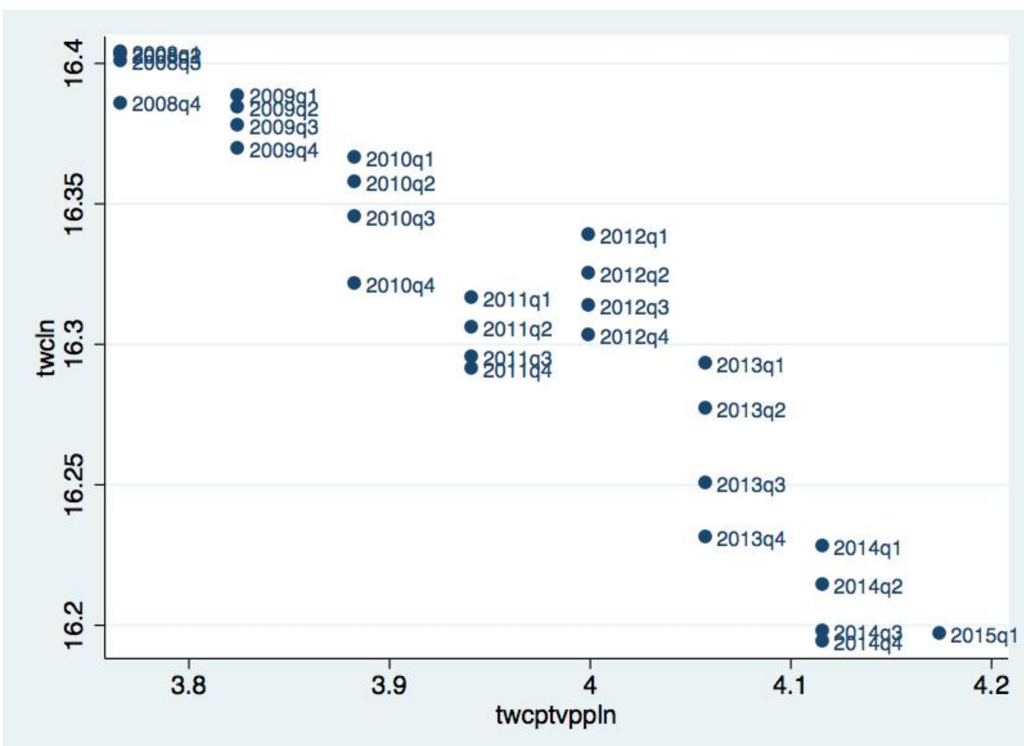


Figure 6. Scatterplot of twcvstwcptvpp



.

Figure 7. Scatterplot of fitted values vs. squared residuals

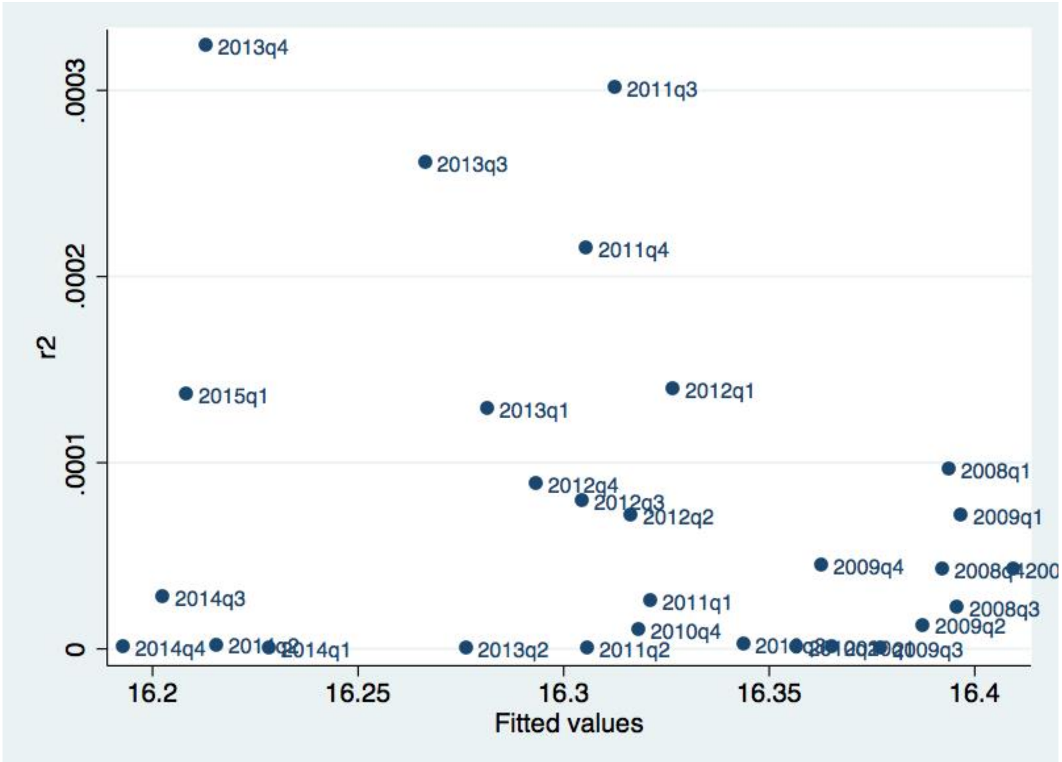
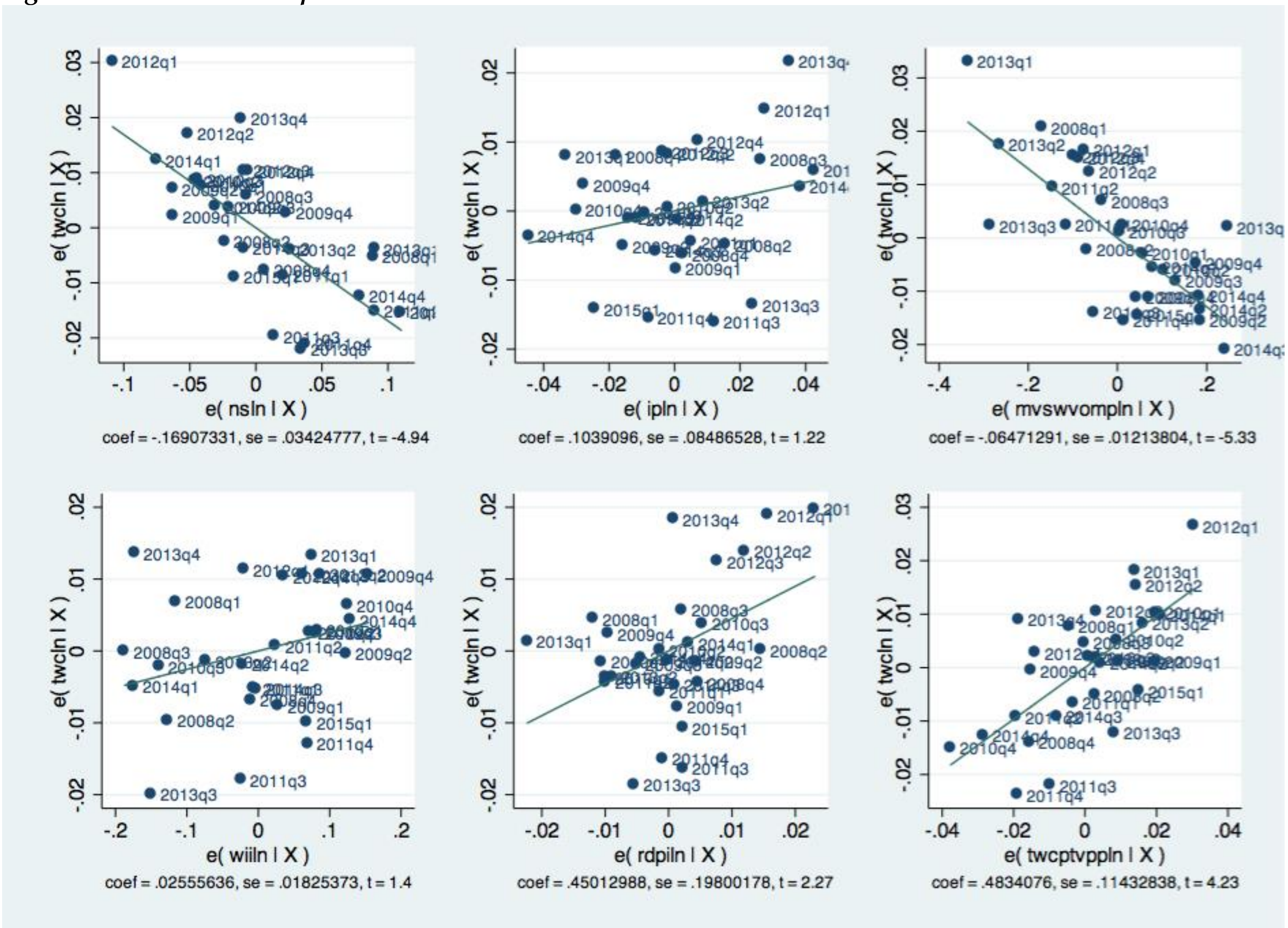

r2
.0003
.0002
.0001
0
16.2
16.25
16.3
16.35
16.4
Fitted values
2013q4
2011q3
2013q3
2011q4
2015q1
2013q1
2012q1
2008q1
2012q4
2012q3
2012q2
2009q1
2009q4
2014q3
2011q1
2008q3
2009q2
2010q4
2014q4
2014q1
2013q2
2011q2
2009q3

Figure 8. Added variable plots



Stem-and-leaf plot for studentized residuals
rs rounded to nearest multiple of .01
plot in units of .01

```
 -2** | 01
 -1** | 97,64
 -1** | 49
 -0** | 93,82,71,59,53
 -0** | 39,15,05
  0** | 01,04,05,08,08,12,15,38
  0** | 54,76,95,96
  1** | 27,42,46
  1** | 56
  2** |
  2** | 66
```

***10 biggest and 10 smallest residuals**

```
     +--------------------+
     |   daters |
     |--------------------|
  1. | 2013q3    -2.01266 |
  2. | 2011q3   -1.966293 |
  3. | 2011q4    -1.64179 |
  4. | 2015q1   -1.485737 |
  5. | 2009q1   -.9275226 |
     |--------------------|
  6. | 2008q2   -.8154608 |
  7. | 2008q4   -.7083201 |
  8. | 2014q3   -.5888675 |
  9. | 2011q1   -.5252014 |
 10. | 2009q2   -.3944471 |
     +--------------------+
```

```
     +--------------------+
     |   daters |
     |--------------------|
 20. | 2010q4   .3776487 |
 21. | 2008q3   .5420073 |
 22. | 2009q4   .7581808 |
 23. | 2012q2   .9456016 |
 24. | 2012q3   .9624779 |
     |--------------------|
 25. | 2012q4   1.270281 |
 26. | 2012q1   1.423427 |
 27. | 2008q1   1.459645 |
 28. | 2013q1   1.560701 |
 29. | 2013q4   2.662936 |
     +--------------------+
```

. Residuals greater than critical value [abs(rs) > 2]

```
     +-------------------+
     |       rs    date |
     |-------------------|
  1. | -2.01266   2013q3 |
 29. | 2.662936   2013q4 |
     +-------------------+
```

Stem-and-leaf plot for leverage

lev rounded to nearest multiple of .001
plot in units of .001

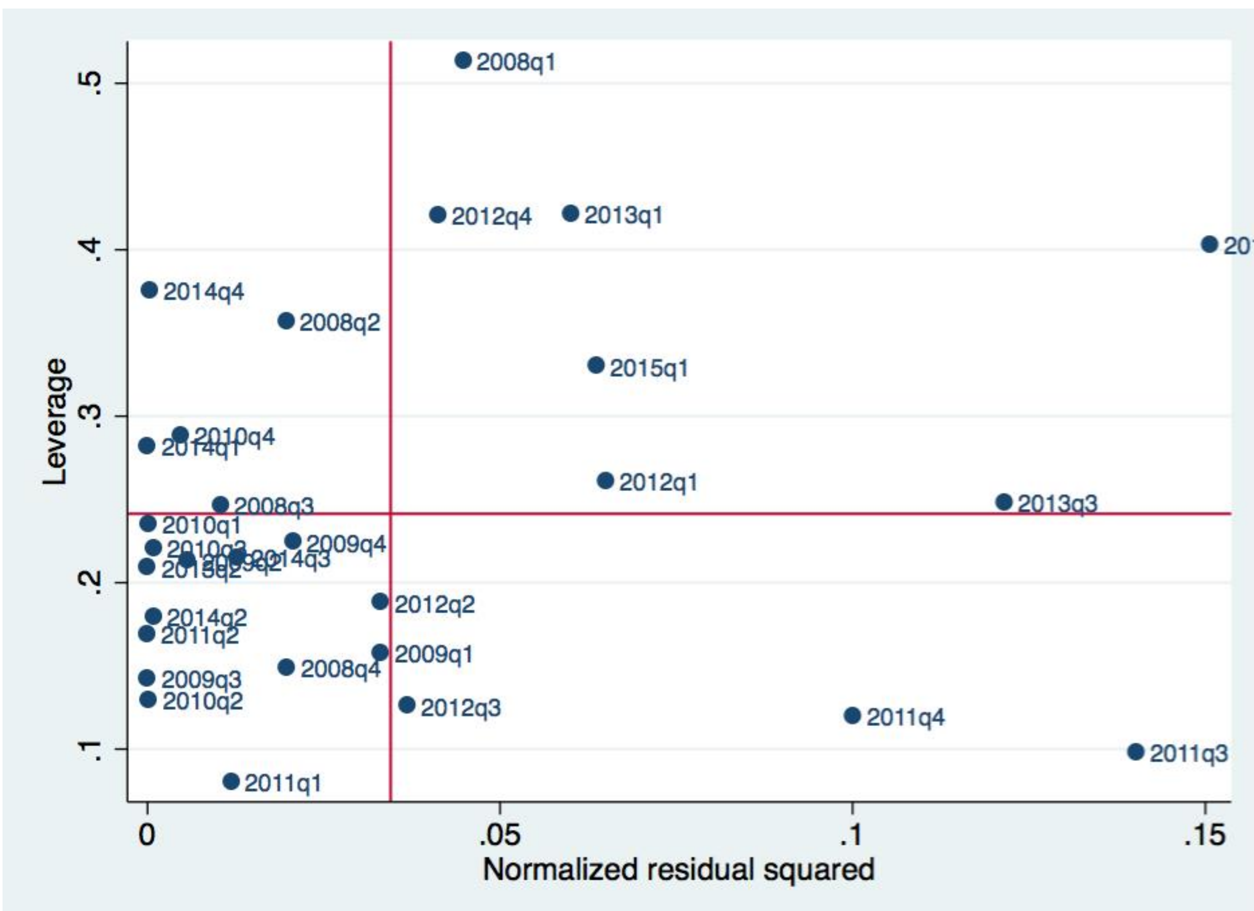
```
0** | 80,98
1** | 20,26,29,42,49
1** | 57,69,79,88
2** | 09,13,15,20,24,35,46,48
2** | 61,82,89
3** | 30
3** | 57,76
4** | 03,21,22
4** |
5** | 13
```

***5 highest observations**

```
    +--------------------+
    |   datelev |
    |--------------------|
 1. | 2011q1   .0804134 |
 2. | 2011q3   .0978393 |
 3. | 2011q4    .119671 |
 4. | 2012q3   .1256676 |
 5. | 2010q2   .1291672 |
    +--------------------+
```

. ***Critical value =**.62068966

Figure 9. Leverage plot



.

DFits

Critical value: abs(dfit)>2*sqrt(6/29)

	twcln	date	dfit
19.	16.25035	2013q3	-1.156157
23.	16.19681	2015q1	-1.042478
26.	16.23116	2013q4	2.185966
27.	16.30291	2012q4	1.082898
28.	16.29297	2013q1	1.332419
29.	16.40372	2008q1	1.498418

Figure 10. Kernel density plot

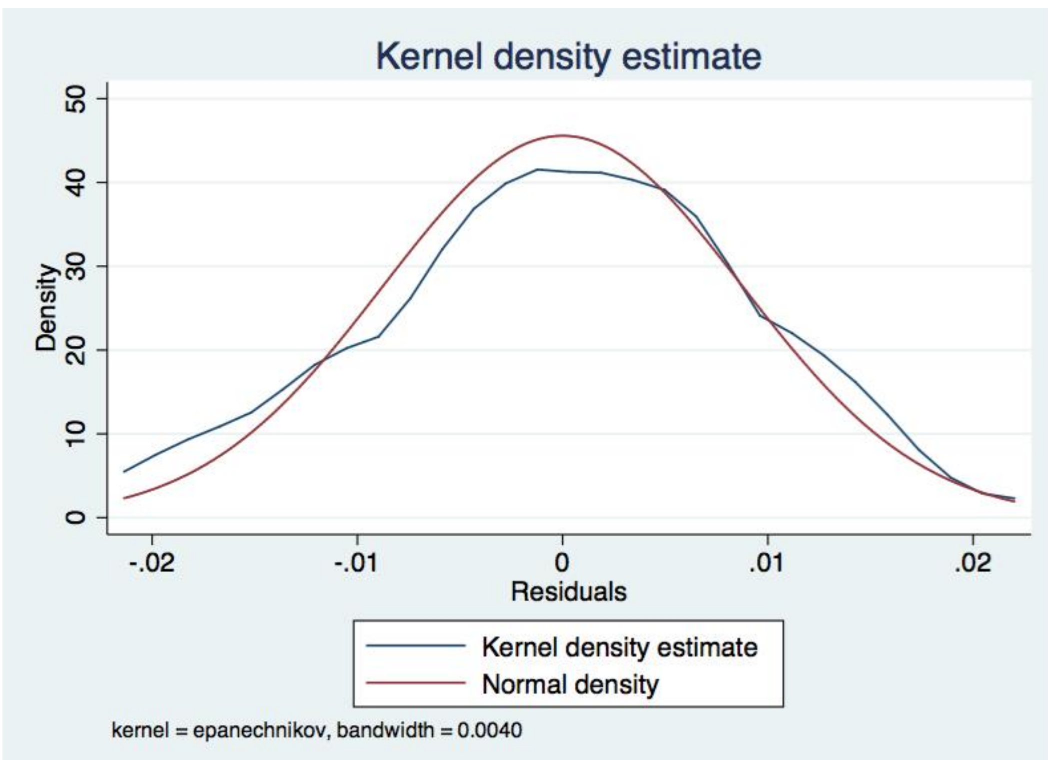


Figure 11. Standardized normal probability plot (pnorm)

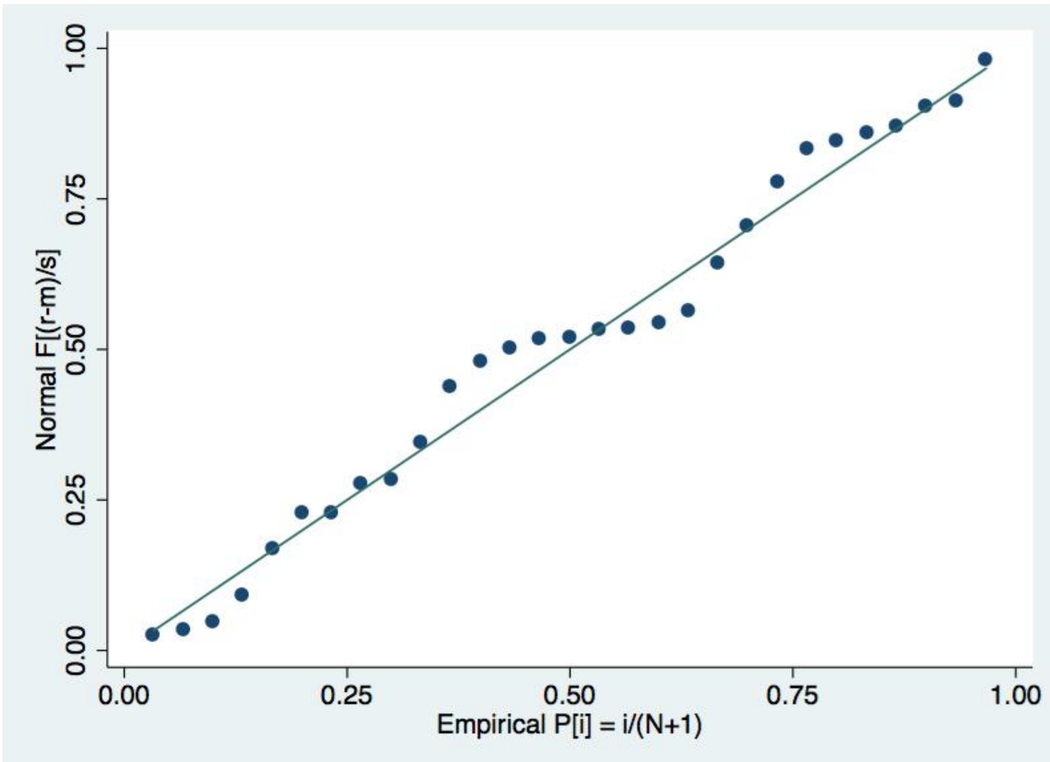
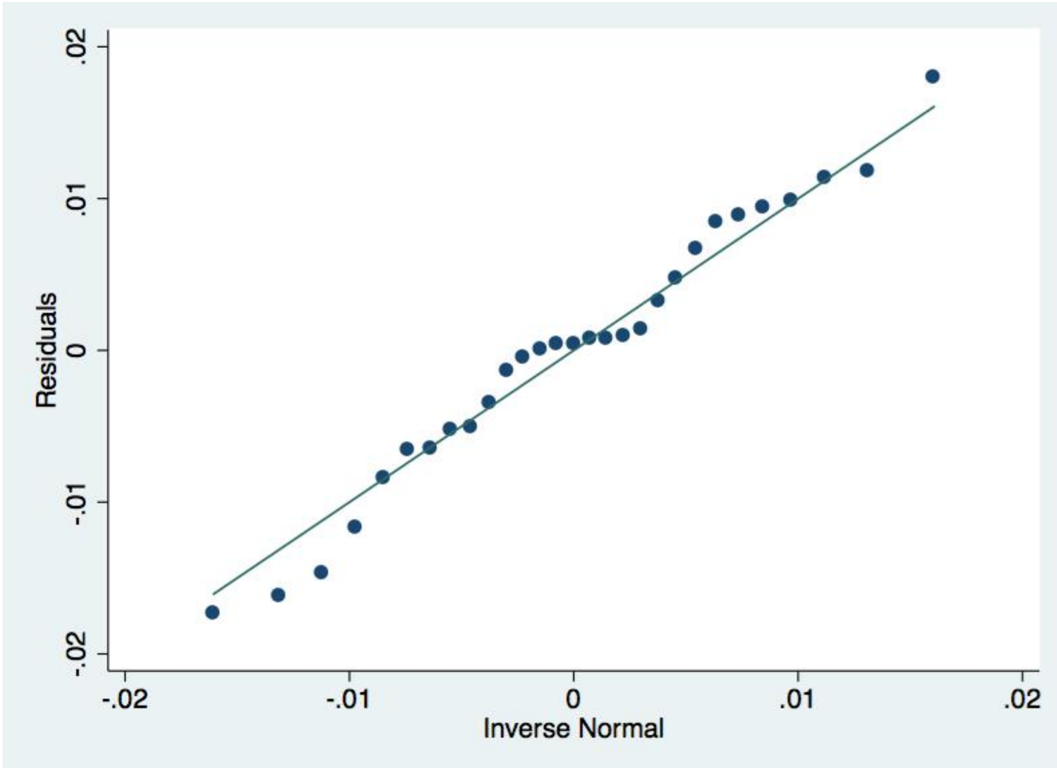


Figure 12. Quantiles of normal distribution plot (qnorm)

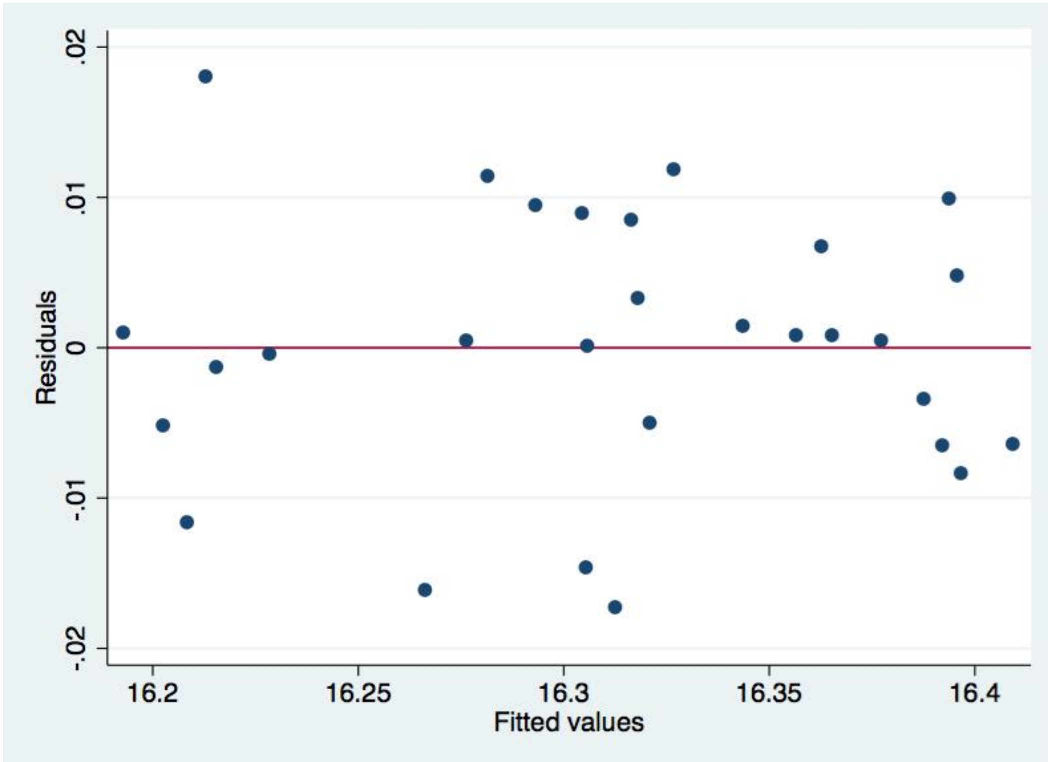


Shapiro-Wilk W test for normality

Variable	Obs	W	V	z	Prob>z
r	29	0.97577	0.751	-0.591	0.72282

.

Figure 13. Residuals vs. fitted values plot



White test

Cameron &Trivedi's decomposition of IM-test

Source	chi2	df	p
Heteroskedasticity	29.00	27	0.3609
Skewness	9.09	6	0.1688
Kurtosis	0.57	1	0.4509
Total	38.65	34	0.2674

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of twcln

chi2(1) = 1.26

Prob> chi2 = 0.2621

Correlation matrix

N=29	twcln	nsln	rdpiln	twcptvgppln	ipln	mvswompln	wiiln
twcln	-						
nsln	-0.9651***	-					
rdpiln	-0.8799***	0.9234***	-				
twcptvgppln	-0.9749***	0.9892***	0.9164***	-			
ipln	-0.8697***	0.9304***	0.7746***	0.9030***	-		
mvswompln	-0.9786***	0.9789***	0.8934***	0.9766***	0.9016***	-	
wiiln	-0.7908***	0.8783***	0.7318***	0.8524***	0.9676***	0.8381***	-

Note: * denotes statistical significance at the 90% level of confidence; ** at the 95% level of confidence; *** at the 99% level of confidence.

Variance Inflation Factor

```
   Variable |       VIF       1/VIF
-------------+----------------------
nsln |    140.14    0.007136
twcptvppln |     57.99    0.017245
ipln |     42.04    0.023786
mvswvompln | 28.72    0.034820
wiiln |     18.59    0.053790
rdpiln |     11.97    0.083532
-------------+----------------------
   Mean VIF |     49.91
```

Variance Inflation Factor (after first-difference transformation)

```
   Variable |       VIF       1/VIF
-------------+----------------------
ipln |      1.36    0.732925
nsln |      1.29    0.773958
twcptvppln1.29    0.775938
wiiln |      1.28    0.783028
mvswvompln1.15    0.871502
rdpiln |      1.11    0.900917
-------------+----------------------
   Mean VIF |      1.25
```

Durbin-Watson Test

Durbin-Watson d-statistic (7, 28) = 2.027149

REFERENCES

BLS (2014). News Release - American time use survey, 2013 results.

Chang, R., R. Kauffman and K. Kwansoo (2013). How Strong Are the Effects of Technological Disruption? Smartphones' Impacts on Internet and Cable TV Services Consumption. 46th Hawaii International Conference on System Sciences. Hawaii.

Comanor, W. S. and B. M. Mitchell (1971). "Cable Television and the Impact of Regulation." The Bell Journal of Economics and Management Science**2**(1): 154-212.

Good, L. M. (1974). An Econometric Model of the Canadian Cable Television Industry and the Effects of CRTC Reulation. London, Ontario, the University of Western Ontario.

Hothi, H. S. and R. G. Bodkin (1980). "An Exploratory Study of the USA Demand for Pay T.V. in the Mid-1970's." Eastern Economic Journal**6**(1): 39-51.

Kieschnick, R. and B. McCullough (1998). Why Do People Not Subscribe to Cable Television: A Review of the Evidence. Telecommunications Policy Research Conference. Virginia.

Liebowitz, S. (2006). "File Sharing: Creative Destruction or Just Plain Destruction?" Journal of Law and Economics**49**(1): 1-28.

Liebowitz, S. and A. Zentner (2015). "The internet as a celestial TiVo: What can we learn from cable television adoption?" Journal of Cultural Economics: 1-24.

Liebowitz, S. J. (2008). "Research Note—Testing File Sharing's Impact on Music Album Sales in Cities." Management Science**54**(4): 852-859.

Liebowitz, S. J. and A. Zentner (2012). "Clash of the Titans: Does Internet use Reduce Television Viewing?" Review of Economics and Statistics**94**(1): 234-245.

Nielsen (2014). The total audience report.

Oberholzer- Gee, F. and K. Strumpf (2007). "The Effect of File Sharing on Record Sales: An Empirical Analysis." Journal of Political Economy**115**(1): 1-42.

Panko, R., G. Edwards, K. Penchos and S. Russell (1975). Analysis of Consumer Demand for Pay Television. S. R. Institute. Menlo Park, California.

Park, R. E. (1972). "Prospects for Cable in the 100 Largest Television Markets." The Bell Journal of Economics and Management Science**3**(1): 130-150.

Reis, F. (2015). Patterns of Substitution between Internet and Television in the Era of Media Streaming -Evidence from a Randomized Experiment, Carnegie Mellon University.

Tryon, C. (2013). On Demand Culture - Digital Delivery and the Future of Movies. USA, Rutgers University Press.

Waldfogel, J. (2009). "Lost on the web: Does web distribution stimulate or depress television viewing?" Information Economics and Policy**21**(2): 158-168.

Waldfogel, J. (2010). "Music file sharing and sales displacement in the iTunes era." Information Economics and Policy**22**(4): 306-314.

Zentner, A. (2006). "Measuring the Effect of File Sharing on Music Purchases." Journal of Law and Economics **49**(1): 63-90.
Zentner, A. (2008). "Online sales, Internet use, file sharing, and the decline of retail music specialty stores." Information Economics and Policy **20**(3): 288-300.