On the Existence of a Behavioral Component to the Business Cycle

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Boston College

The Graduate School of Arts and Sciences

Department of Economics

ON THE EXISTENCE OF A BEHAVIORAL COMPONENT TO THE BUSINESS CYCLE

A Dissertation by

ZHAOCHEN HE

submitted in partial fulfillment of the requirements

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Abstract

On the Existence of a Behavioral Component to the Business Cycle, by Zhaochen He. Thesis Committee: Donald Cox (Chair), Peter Ireland, Mathis Wagner

This dissertation consists of two essays which address the origins of the business cycle. In particular, it asks: to what extent do behavioral or psychological effects, famously termed “animal spirits” by John Maynard Keynes, contribute to the amplification of business cycle fluctuations.

The first essay, titled “The Labor Market Effects of Bad Economic News”, examines the effects of economically pessimistic newspaper articles on hiring and employment patterns. Combining information on newspaper subscriptions with automated content analysis of newspaper articles, the paper reconstructs the flow of pessimistic news across the United States during the past recession on a county-by-county, quarter-by-quarter basis. This high resolution map of pessimistic news delivery is then used to estimate the causal impact of media pessimism on labor market outcomes. Exposure to negative news is found to suppress hiring and total employment during the early stages of the recession by up to 40% compared to pre-recession levels; overall, media pessimism can account for some 7% of jobs lost between 2007 and 2010. Further analysis of Google search data suggests that this contractionary effect is mediated by changes in public attitude caused by exposure to pessimistic stories in the media.

Importantly, this study considers only articles which report negative news about the state of the *national* economy, rather than stories which focus on local events. It argues that the prevalence of such news stories affects local labor market conditions, but is unlikely to be affected *by* such conditions. This approach helps to address the simultaneity issues which have dogged previous research on the topic.

The second essay, titled “Uncertainty and Risk Averse Firms in DSGE” a develops theoretical framework to rationalize the previous paper’s empirical results. This paper solves a simple general equilibrium model in which firms are risk averse over future profits in a manner analogous to household risk aversion. It shows that response to increased economic uncertainty - particularly uncertainty with regards to future consumer demand, economies with risk averse firms are likely to undergo a business cycle contraction.

This result also addresses a long standing problem in the RBC literature; namely, how to generate a contraction with a keynesian demand side shock. In most models with risk averse utility-maximizing households, a reduction in aggregate demand due to consumer-side changes is expansionary. The paper argues that by introducing firm-side risk aversion into the model, this counter-intuitive behavior can be corrected in a realistic and parsimonious manner.

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Introduction

There are two broadly differing schools of thought on the origins of recession. The real business cycle paradigm, ubiquitous in modern macroeconomic research, posits that economic booms and busts constitute efficient reactions of the economy's primary markets to changes in economic fundamentals. These changes, or "shocks", can come in a variety of forms, the most popular of which is a change to the underlying production technology. In the context of a DSGE model, such shocks can lead to co-movement between macroeconomic aggregates such as output and consumption that match observations of the real economy.

In contrast to this viewpoint, a behavioral interpretation of the business cycle posits that changes in economic fundamentals, alone, are are insufficient to explain macroeconomic fluctuations. This viewpoint is perhaps best summarized by President Franklin Roosevelt's famous remark the midst of the great depression, "the only thing we have to fear is fear itself". In economics, this perspective is associated with a number of terms; Keynes's famous "animal spirits", but also the close related ideas of economic sunspots and indeterminacy. While these notions differ somewhat from one another in their details, they all suggest that subjective psychological factors such as fear and uncertainty also govern macroeconomic activity. Further, while it's unclear how many contemporary macroeconomists take such ideas seriously, a behavioral interpretation of recessions is very prevalent among laymen and policy makers, and is widely reported in the mass media.[1]

Distinguishing between these two viewpoints is not only a matter of understanding the fundamental origins of the business cycle. It also significantly affects the way we look at government intervention. In an world governed by efficient reactions to shifting economic fundamentals, government intervention is limited to manipulation of markets through real, bottom-line effects. A tax break increases consumer's disposable income, stimulating aggregate demand. A change in the money supply increases real wealth because prices are sticky. In both of these cases, it's the government's physical impact on a market, facilitated by real economic transactions, which alters the course of the slumping economy. But in a world where fear itself is contractionary, government policy with regards to the economy needs to be *marketed*, since agent's subjective beliefs about that intervention (and it's effectiveness) have real economic consequences. While some politicians have clearly incorporated this idea as part of their anti-recession strategy - with F.D.R's fireside chats as an early example, many (including, Former treasury secretary Hank Pauson) have argued that government intervention in the economy is poorly communicated to the public. From Alan Greenspan's famously cryptic reports to congress, to the widespread unpopularity of the TARP bailout despite overwhelming support among economists, evidence of this disconnect is easy to find.

This paper seeks to test the behavioral hypothesis of business cycle fluctuations using both applied and theoretical tools. To see how, it's important to recognize that the behavioral hypothesis described above consists of two separate but interdependent components. The first is the subjective attitudes of microeconomic agents with regards to the economy and their expectations of it's future. This includes elements which are already incorporated into standard models, such as consumers' aversion to risk. But understanding the attitudes of individual agents isn't enough. After all, such attitudes are never formed in a vacuum - agents constantly receive signals from other agents, and from organized institutions such as the government and the mass media. To understand the behavioral component to the business cycle, we must also think about the social mechanisms which govern how individual attitudes are formed and how they spread throughout the economy.

The empirical paper which forms the first part of this dissertation looks primarily at the social component - specifically, the role the mass media played in the past two recessions. The theoretical paper in the subsequent chapter focuses on the individual component - specifically, the effects of risk aversion of the side of firms. But whatever the mechanism, these papers have one thing in common: they show that "real" economic factors don't entirely determine the economy's reaction to a shock; that something psychological or sociological is also implicated.

[1] See the appendix and the introduction of Chapter 1 for more evidence of this.

Part I

The Labor Market Effects of Bad Economic News

1 Introduction

This paper asks whether the mass media can amplify business cycle fluctuations. Consider the following scenario: a consumer reads an article in a major U.S. newspaper warning of an oncoming economic downturn. Uncertain about the future, and worried about her job security, she postpones buying a new car until the next year. At a local car dealership, a sales manager reads the same article. Now pessimistic about consumer demand, he delays the planned hiring of new workers. In taking these actions, both agents have made it more likely that the very recession they fear will come to pass. If many agents across society respond in a similar matter, the economy may begin to sputter - exactly as the article warned.

The remainder of this paper will refer to the above tale as the *media-feedback hypothesis*. Is such a scenario really possible? While forms of this story are often discussed by policy-makers and the public, the effects of media sentiment on business cycle outcomes is poorly understood. A robust literature within political science has established that the news plays a pivotal role in informing the public about economic conditions (Goidel et. al., 2010). But does the news media's coverage of events merely *reflect* economic reality, or does it help shape that reality? If the media does exert a causal role, how large is it's influence?

Previous research hints that these questions are more than speculative. Numerous studies have found that the news affects people's attitudes towards the state of the economy, even after controlling for one's personal economic situation (Fogarty, 2005; Goidel & Langley, 1995). What's more, both applied and theoretical papers have suggested that such attitudes may affect macroeconomic preformance (Matsuska & Sbordone, 1995; Ludvigson, 2004; Taylor, 2007). Taken together, this evidence implies that the news may play an independent role in shaping economic outcomes.

However, no papers have yet tried to directly estimate the effects of media pessimism on economic performance. Any attempt to preform such an estimation must overcome the challenge of simultaneity - since the media is obligated to report on economic events, it's difficult to differentiate between negative news causing outcomes and negative outcomes causing the news. This issue is exacerbated by the fact that the media's voice has only been characterized at aggregate levels - for example, counting the number of times the word "recession" appears across major news sources. While such measures are almost always correlated with GDP, it's difficult to control for the presence of unobserved confounds when time is the only source of identifying variation. To address these limitations, this paper constructs a unique panel dataset describing the delivery of pessimistic economic news at county and quarter levels. It also preforms content analysis of that news in order to identify and remove stories which merely report local economic conditions. As I'll argue in greater detail, these innovations help us to identify the media's causal effect.

But before delving into this paper's methodology, I want to emphasize why economists should care about the media's role at all - particularly macroeconomists. The feedback of pessimistic information is frequently described in the public discourse as playing a causal role in business cycle contraction. For example, consider the following statement made by Warren Buffet to the shareholders of Berkshire Hathaway in the midst of the recent financial crisis:

> "By the fourth quarter, the credit crisis, coupled with tumbling home and stock prices, had produced a paralyzing fear that engulfed the country. A free-fall in business activity ensued, accelerating at a pace that I have never before witnessed. *The U.S. – and much of the world – became trapped in a vicious negative-feedback cycle. Fear led to business contraction, and that in turn led to even greater fear.*" [Emphasis mine]

Business leaders and policy-makers often express similar sentiments; the appendix cites a range of voices, including Federal Reserve chairman Ben Bernanke and president Barack Obama, all echoing Buffet's statements. But despite their popularity, such explanations are usually *not* invoked in standard business cycle models, which instead view recession as an efficient response to fluctuations in economic fundamentals (Tayler & Woodfood, 1999). While effects consistent with Buffet's account can appear in certain parametrizations of these models, such "sunspot equilibria" are generally considered to be pathological (Farmer, 1999). These

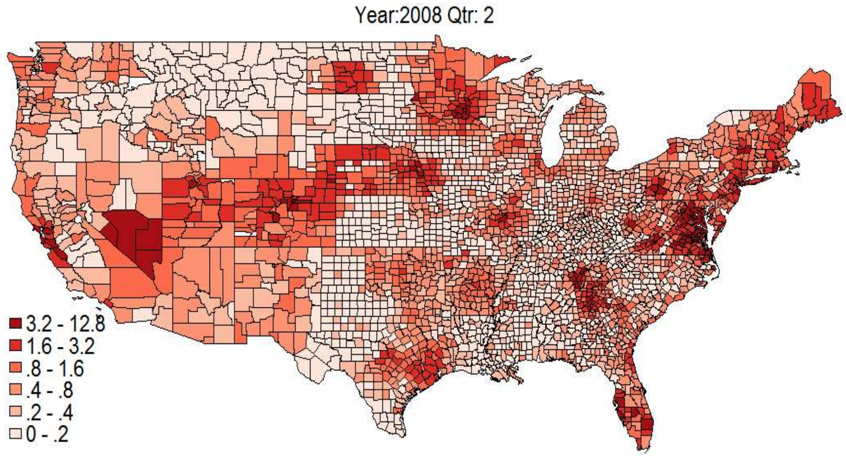


Figure 1: Pessimistic Articles per Person - 2nd Quarter, 2008

competing explanations represent two fundamentally different notions of business cycle dynamics; it's important that economists can distinguish between them on the basis of empirical evidence.

How does the media's effect bear on this issue? Since the news media is the public's primary source of economic information, it almost certainly plays a pivotal role in the type of feedback cycle described by Buffet above. In essence, the scenario in the first paragraph of this paper is simply an instance of Buffet's claim, with pessimistic news catalyzing the type of fear-driven cycle he describes. Detecting an independent effect of media pessimism would imply that Buffet's theory, and similar accounts of business cycle dynamics, deserve to be taken more seriously.

What's more, role of the media has implications for public policy, since government action during a recession is widely reported by the news. Traditional views of fiscal stimulus emphasize the effects of government spending on aggregate demand. But Konstantinou & Tagkalakis (2009) find evidence that such interventions also affect consumer and business confidence. It may be that government policy has a stimulatory effect through this channel, even if the direct intervention fails to have the intended consequences.

A Natural Experiment This paper will estimate the media's influence by exploiting idiosyncrasies in the way that news is delivered across the United States. To see how, consider the following thought experiment. Take a number of counties in the U.S. that are facing identical economic conditions. Now imagine censoring the flow of news into each county. Some counties will be fed entirely optimistic news, others counties pessimistic news, still others neutral coverage or a blend of positive and negative voices. After a while, we will observe how relevant economic variables such as hiring or employment have changed in these counties. Since the counties differ only in the news that they received, such an experiment would allow us to identify the causal effect of media pessimism on economic outcomes.

While this procedure is obviously infeasible, this paper argues that nature has already conducted a version of this experiment for us. Figure 1 displays the distribution of *economically pessimistic newspaper articles per person* delivered to counties across the U.S. in the second quarter of 2008. This unique dataset was built by combining data on newspaper subscribership with a count of the number of pessimistic articles printed by each those papers; it is the first time that the flow of pessimistic economic news has been understood at sub-national resolution. The great variation in the level of media-pessimism between counties exists for two reasons. First, different counties rely on different newspapers; second, those papers vary in pessimism between one another and over time. By carefully examining the relationship between this pattern of pessimism and labor market conditions in each county, the causal effect of media sentiment can be inferred.

The success of this procedure relies on overcoming two important confounds. First, unobserved variables may jointly affect media-pessimism and economic performance. For example, suppose that the New York Times is relatively more optimistic than other sources of news. Suppose further that managers who read the New York Times tend to be more optimistic, and thus, more likely to hire a worker. We would then expect to see a positive correlation between counties receiving optimistic news and counties with more hiring. This correlation would be driven by differential reliance on the New York Times as a news source rather than a causal relationship between optimism and hiring.

Second, the very notion of feedback implies that media pessimism is both a cause and a result of poor economic performance. This simultaneity complicates our estimation procedure. For example, suppose a factory in a given county shuts down, and that this event is covered by a widely read local newspaper. That county would then receive a positive shock to both unemployment and the level of pessimistic news. However, this correlation would result from a bad economy causing bad news, not the reserve.

The panel data-set constructed in this paper can help overcome both of these difficulties. As we'll see, the empirical results below are robust to county and state-by-year fixed effects as well as a battery of demographic controls. In section 3.4, I will argue that the most important classes of unobserved heterogeneity can be absorbed by these covariates. At the same time, this paper introduces a number of innovations to deal with simultaneity. The most important of these involves textual analysis of the articles themselves to identify and remove stories which refer to local employment conditions. This will allow us to see whether differential exposure to news about the state of the *national* economy can affect local outcomes. Since any single county has only a marginal effect on the national economic state, this analysis would reflect the effect of news on outcomes, not the vice-versa.[2]

Summary of Findings Before describing my estimation procedure in detail, I will summarize the most important findings of this paper. The first result is hinted at by figure 1; the spatial distribution of pessimistic news, which until now has never been characterized, is extremely heterogeneous. During the height of the past recession, media pessimism varies by several orders of magnitude between counties in the same quarter. This cross sectional variation is most prominent at small geographic scales, and it's variance dwarfs the dispersion of underlying economic variables such as unemployment or output. In both time and space, the *signals* that agents receive about the economy fluctuate far more wildly than its actual state.

Second, the causal effect of pessimistic news on county employment rates was estimated at roughly 0.2 percentage points per article per person. This estimate would amount to a reduction in employment of roughly 600,000 jobs from 2007 to 2010, or some 7% of the total change in employment over those three years. The effect of the media was particular pronounced in the early stages of the recession, where it can account for up to 40% of the reduction in employment in a given quarter. Additional analysis of Google search data shows that the flow of pessimistic news into a county increases the number of google searches for the word "recession" in that county. This suggests that the labor market effects described above are mediated by changes in public sentiment resulting from exposure to pessimistic news.

Third, the media's effect on total employment is mostly driven by it's effect on job creation. The point estimates for hiring are negative and precisely estimated across all specifications, while the effect on separations is ambiguous in sign and tends to be statistically insignificant. This result is consistent with recent theoretical and empirical studies that highlight the importance of job-finding as the primary driver of countercyclical employment patterns (Shimer, 2007). It also argues that simultaneity isn't driving our estimates, as layoffs are far more newsworthy than simply a suppression of hiring.

Forth, the causal of effect of pessimism appears to vary significantly across industries. Construction, retail trade, and finance are among the industries most sensitive to pessimistic news, while agriculture, entertainment, and health care show the smallest response. The sensitivity of an industry to media pessimism appears to be uncorrelated with that industry's level of newsworthiness, but positively correlated with the contraction in output experienced by that industry during the recession. This also suggests that the effect is caused by industries cutting employment in anticipation of a reduced demand, rather than the mere reporting of poor labor market conditions.

Finally, there is evidence of media saturation - once it becomes widely known that a recession is in progress, pessimistic news is no longer a significant driver of labor market outcomes. For example, bad news has a strong negative impact on employment and

[2]Of course, there are caveats to this line of thought which need to be dealt with individually. I will be discussing these issues in detail in the identification section below.

hiring during the first year of the recession. Subsequently, the effect becomes weaker, less significant, and in fact is slightly positive for some specifications.

Together, these results bear on more general questions regarding the business cycle and how it should be understood. The discussion section addresses the relationship between the empirical findings above and macroeconomic theory. In particular, it describes the connection between media-feedback, sunspot equilibria, and "animal spirits", and asks whether it's possible to reconcile the presence of a media effect with the assumption of rational expectations.

The remainder of this paper is organized as follows. Section one reviews the existing literature and describes some of the common difficulties in identifying the effects of sentiment - either on the part of the media, or consumers and business owners. Section three describes my empirical methodology with a focus on addressing these identification problems. Section four presents my results in detail, and section five discusses the relationship between these results and macroeconomic theory.

2 Previous Literature

As yet, no papers have tried to directly estimate the effects of media pessimism on economic performance. However, the existing literature, if taken as a whole, suggests that attitudes in the news may affect the course of the business cycle. This research falls into two categories. First, a robust line of research in the political science literature documents the effects of media pessimism on consumers attitudes. These papers have established that individuals rely on the mass media for economic information (De Boef & Kellstedt, 2004; Wu et. al, 2002; Hetherington, 1996; among many others), that citizens pay more attention to economic news during a recession (Soroka, 2006; Hester & Gibson, 2003; Headrick & Lanoue, 1991, Doms & Morin, 2004), and that the news has an independent effect on sentiment even after controlling for real economic conditions (Goeidel et al., 2010, Fogarty, 2005; Goidel & Langley, 1995; Harrington, 1989).

As an exemplar of the methods employed in these papers, consider Geoidel et al., 2010. In this paper, the authors analyze the effects of TV and print media on consumer sentiment in Louisiana. They use data from the Louisiana Consumer Confidence Survey; critically, this survey contains questions not only about consumer's economic attitudes, but their exposure to economic news in both TV and newspapers. They subsequently measure the pessimism of popular news sources in Louisiana (both on TV and in print) by hiring students to manually watch or read samples from those sources. They find that exposure to pessimistic news on television has a significant impact on individual's expectations of personal and family finances, while exposure to bad news in the newspaper seems to impact their assessment of U.S. business conditions. Importantly, these results hold after controlling for each individual's demographic characteristics and personal economic situation.

In a related paper, Haller and Norpoth (1997) find that close to half of Americans self-report *no* economic news exposure, but that their expectations generally track respondents with positive exposure. This suggests that the attitude of the media is subsequently transmitted by word-of-mouth or other channels of communication, and may have an impact beyond the immediate watchers or readers of that news.[3]

Within the political science literature, a clear consensus have developed that the media has an effect on individual's economic sentiments. But do those changes in sentiment translate to changes in macroeconomic conditions? This question is the subject of a number of papers within economics, and is more controversial. These papers can be divided into three categories: first, surveys at the micro-level which establish a relationship between confidence and the behavior of individual firms or consumers (Silverstone & Mitchell, 1995); second, theory papers which attempt to endogenize business or consumer confidence into business cycle models (Danthine et. al, 1998; Fagiolo & Roventini, 2004; Sell, 2005), and third, empirical papers which directly estimate the effects of consumer or producer sentiment on economic outcomes.

This third line of papers is most similar to my research, and has been the subject of considerable debate. Much of this literature tries to relate measures of public attitude (such as University of Michigan's consumer confidence index) with macroeconomic

[3]To be fair, the correlation between news watchers and non-watchers could also be explained third factors which jointly determine media coverage and general public attitude. This type of issue isn't fully addressed in the Haller and Norpoth paper, but will be addressed in this paper.

variables such as spending or output, usually through a vector-autoregression. The idea is to see if consumer confidence can predict future changes in the target macroeconomic variable after other factors influencing that variable (say, stock market performance or housing prices) are included in the specification. Some of these papers find a positive effect of consumer confidence on output (Matsuska & Sbordone 1995, Golinelli & Parigi 2004, Hall, 1993) but others find that the effect disappears if additional covariates are taken into account (Desroches et al., 2002, Loria and Brito, 2004, Adams & Green, 1965). This disagreement highlights an important limitation of using nationally aggregated measures of consumer attitude - with identifying variation provided by time alone, it's always difficult to establish whether pessimism is causing poor economic performance, or whether an omitted factor is jointly affecting both.

This paper differs from the line of research above in two significant ways. First, it focuses on the attitude of the media rather than the attitude of individuals. The literature cited above has shown a clear relationship between media sentiment and consumer sentiment, but the former can be measured without the use of subjective surveys. More importantly, while measures of consumer confidence are only available as a national time series, this paper disaggregates media sentiment by county. With panel data in hand, the introduction of fixed effects can control for many kinds of potential confounds at once. As we'll see below, the effects of media-pessimism can be identified using only variation between counties in the same state and quarter.

Lastly, the paper most similar in methodology to this one is Engelberg & Parsons (Journal of Finance, 2011). Here the authors are interested in the effects of the media on financial markets. They find that local trading is strongly related to the local reporting of industry specific news, and that regional idiosyncrasies in media coverage (for example, weather events that affect newspaper delivery) affect trading in those areas. My paper also uses regional variation in news delivery for identifying variation - albeit of a different type - but it focuses on macroeconomic performance rather than stock market activity. In addition, it analyzes data from nearly all U.S. counties and newspapers, rather than a subset of urban areas and corresponding local papers.

3 Empirical Strategy

3.1 Measuring the Delivery of Bad Economic News

This paper's methodology begins with measuring the delivery of pessimistic news across the United States at high resolution. Due to data availability, I focus on the newspaper medium rather than television, radio or internet news sources. While newspapers have experienced declining readership in the past decade, Gallop's annual survey of the news media (Figure 2) reveals that roughly 31% of individuals still report getting yesterday's news from the paper - this compares with 34% for radio and 58% for television news . As discussed in the literature review, Goeidel et. al find that newspapers actually have a stronger impact on individual's assessment of the U.S. business climate than television news. Given this, it seems safe to assume that newspapers have a significant, albeit declining role in shaping the public's economic sentiment.

To date, newspaper's attitudes with respect to the economy have only been characterized on limited scale. For example, Alsem (2008) uses human readers to count the number of pessimistic articles appearing in major dutch newspapers between 1998 and 2002. There are two limitations with this kind of measure. First, relying on manual reading means that only a small number of dates and papers can be surveyed - the dutch study included only two major papers and used only articles appearing on the first Saturday of each month. More significantly, this approach doesn't take into account geographic dispersion in newspaper readership. With the exception of a few nationally distributed sources, U.S. papers are highly regional in nature with many publications possessing subscribership in only a few counties. This means that characterizing the pessimism of any single source is only informative of the news delivered to a small region.

The scope of this analysis is considerably broader. By using an automatic search, I identify pessimistic articles across almost every U.S. newspaper for all dates in the past two decades. I then combine this measure with geographic data on newspaper subscribership; the result is a quarterly reconstruction of the flow of negative articles into each U.S. county. The next three sections describe the details of this process, beginning with how the pessimism of a given newspaper was established.

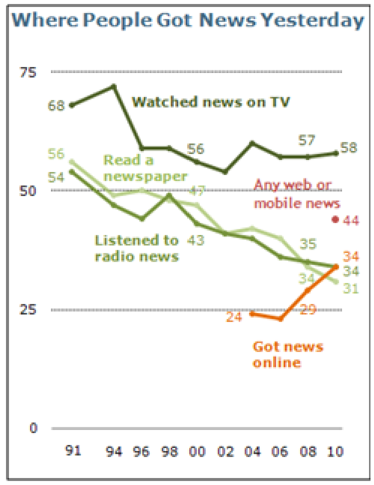


Figure 2: Gallop Poll (2010) - Relative Popularity of Various Media Types

How pessimistic was each newspaper in a given period? U.S. newspaper articles with a negative economic outlook were identified using an "indexed search" in the Lexis-Nexis Academic database. Lexis-Nexis catalogs the full text of almost all U.S. newspapers and scores each newspaper article on a scale of 1 to 100 for a number of topics, such as "economic decline", "unemployment", "local and regional", or "United States". After experimenting with combinations of these terms, search criterion were found which could consistently identify pessimistic articles. Importantly, it was possible to ignore *optimistic* articles by avoiding stories tagged with "economic growth" or "economic recovery".

This process identified some 67,000 economically pessimistic articles across 716 newspapers over the past two decades. Of these sources, roughly one-fifth (151 newspapers) reported more than one-hundred pessimistic articles over the entire time-frame. These 151 major sources account for more than 85% of the total volume of pessimistic stories. Figure 3 displays how these stories are distributed in time, both for all U.S. newspapers and for the five sources reporting the greatest number of stories. It's clear from this data that the volume of media pessimism closely tracks the course of the business cycle. It's also clear that there is significant variation in the level of pessimism between sources, both in terms of the average number of stories reported and the timing of those stories.[4] These trends are consistent with previous studies which have found that the volume of pessimistic news is anticyclical.

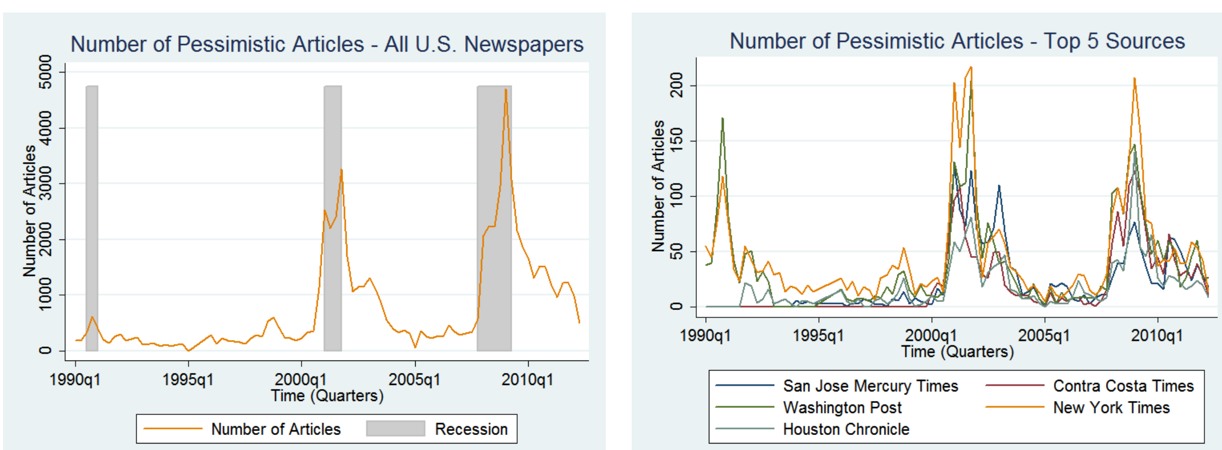


Figure 3: Pessimistic Newspaper Articles Per Quarter

[4]The previous two recessions are easy to identify in this figure; the early 90's contraction is also barely visible. Lexis-Nexis data is incomplete for some newspapers before 1991, therefore, this third recession is appears less prominently

What do these articles talk about? Table 1 displays the most frequently used words in the identified articles. The topic of these stories ranges widely. Some refer to specific economic indicators or events, such as the BEA's quarterly GDP estimate or the collapse of Lehman Brother holdings. Most articles don't explicitly refer to economic indicators, but instead describe how declining economic conditions are affecting individuals or institutions, and how those individuals or instruction are coping with the changes. A minority refer to local layoffs or plant closings - as will be discussed later, these articles pose problem with our identification strategy and will be eliminated from the sample.

Common Words in Identified Articles

Rank	Count	Word	Rank	Count	Word
1	4070	economy	11	1448	sales
2	3138	state	12	1341	plan
3	2990	new	13	1300	market
4	2347	business	14	1239	recession
5	2336	economic	15	1238	cut
6	2293	budget	16	1213	year
7	1878	tax	17	1206	county
8	1715	cuts	18	1174	area
9	1697	jobs	19	1155	rate
10	1455	city	20	1132	job

Table 1: Frequent words in identified articles, excluding common english words.

Who reads what newspapers? County level data on newspaper subscribership was obtained from the Alliance for Audited Media. The AAM is a non-profit organization that collects subscribership data for print media sources and sells this information to advertisers and academics, not unlike the ratings data collected by Neilsons for television programming. For each U.S. county, this dataset breaks down the number of subscribers by newspaper for all papers with more than fifty subscribers in the county. Subscription to each news source is further disaggregated by edition - for example, Saturday, Sunday, and weekday subscriptions are separately counted. Data was available for the years 2006, 2009, and 2012. Subscribership for the years between these dates, as well as dates going back to the year 2003 was extrapolated using a linear interpolation. Other interpolation schemes were tested for this purpose, however, no significant differences were found the subsequent empirics. Including only dates subsequent to 2006 was also tested, again with no significant difference in results.

An additional caveat involves subscribership data for three major newspapers: the New York Times, USA Today, and the Wall Street Journal. The AAM considers these sources to be "national papers" and collects subscribership data for these papers annually at the DMA level. A DMA refers to a "designated market area", a set of standardized regions frequently used by advertisers. Each DMA is comprised of a large number of zip-codes; there are roughly two hundred such regions in the US, with each region corresponding roughly to 15 counties. County level subscribership for the DMAs was interpolated by using each county's population share within that DMA.

Figure 4 summarizes the subscriptions information contained in the AAM dataset. Overall, newspaper circulation size is distributed exponentially with a median of subscribership of roughly 37,000. While the three papers mentioned above are circulated nationally, these papers are a glaring exception in a landscape of otherwise highly local publications. Of the more than one thousand sources tracked by the AAM, only twelve have positive circulation in more than a hundred counties. In fact, the majority of papers have a readership which extends for only a handful counties and may have as few as several thousand readers. This patchwork of regional papers, all reporting a differing levels of negative news, is what creates the great geographic dispersion in pessimism displayed in figure 1.

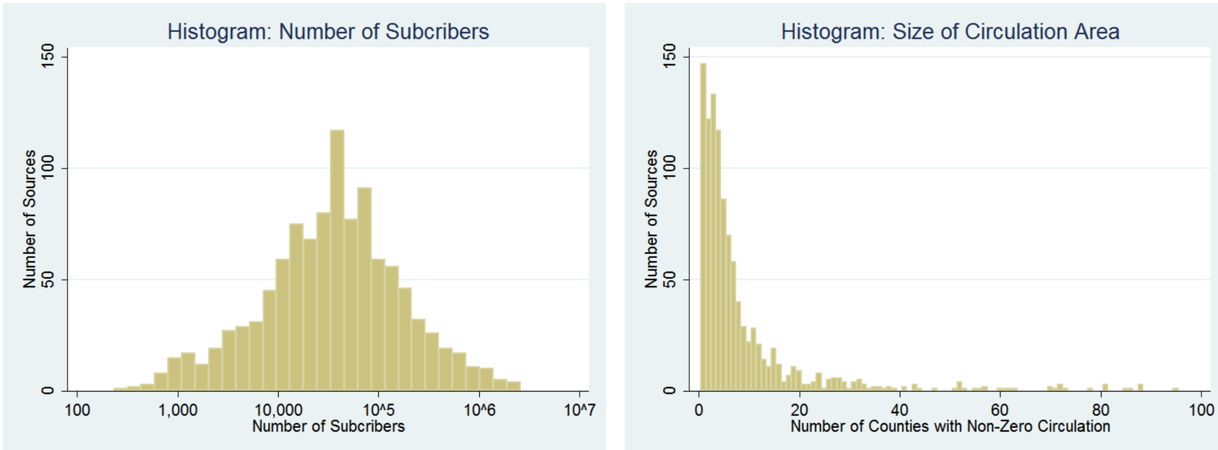


Figure 4: Nature of Newspaper Sources

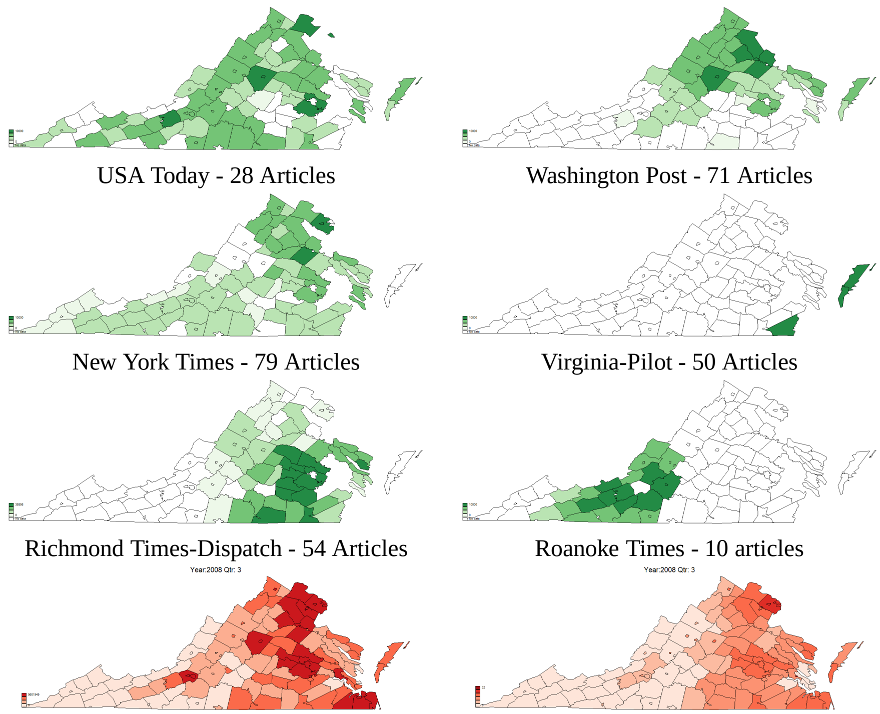
3.2 Computing the Flow of Pessimistic News into Each County

With these data in hand, the total flow of pessimistic news into each county was computed in the following manner. First, the newspapers listed in both the AAM and the Lexis Nexis database were cross-indexed. This process matched 70% of all sources and 84% of all articles in the two datasets. Second, the date of each article was used to establish the edition in which that article appeared (i.e., Saturday edition vs. weekday). Then, for each county, the number of stories in each edition-source was summed, weighted by the number of subscribers to that edition-source. Finally, this quantity was divided by the county's total population. The resulting variable is called articles per person (APP) and is the primary explanatory variable considered in this paper. This quantity represents the average number of newspaper articles delivered to a county per capita. Obviously, there is no way to tell if every individual reads each article; if they do, this variable would represent the average number of pessimistic stories read by a person living in a given county per quarter.

$$APP_{i,t} = \frac{1}{population_{it}} \sum_{j=1}^{J} \sum_{e=1}^{E} Subscribers(i,t)_{j,e} * Articles(i,t)_{j,e}$$

j = 1...*J Sources*
e = 1...*E Editions*
i = 1...*N Counties*
t = 1...*T Quarters*

As an example, figure 5 displays the above calculation for the state of Virginia. The top six panels maps the subscriptions rate to the weekday edition of the most widely read newspapers in Virginia and displays the total number of pessimistic articles printed by each of those sources. For simplicity, I've summed each of these sources across editions; the totals below refer to total subscribers regardless of edition. The bottom diagram displays the flow of pessimistic news based these data, with the total count on the left and the per-person count on the right.



USA Today - 28 Articles | Washington Post - 71 Articles

New York Times - 79 Articles | Virginia-Pilot - 50 Articles

Richmond Times-Dispatch - 54 Articles | Roanoke Times - 10 articles

Total Pessimistic Articles Delivered | Articles Per Person (APP)

Figure 5: Constructing a Measure of Media-Pessimism

3.3 Jobs Data

Detailed data on employment, hiring, and separations was acquired from the Quarterly Workforce Indicators (QWI) released by the U.S. Census Bureau. Labor market behavior was chosen as the outcome of interest in this paper for several reasons. First, detailed data about the labor market is available at county and quarterly frequencies. Most measures of consumer behavior such as personal savings are reported only annually or as a national aggregate. Second, some properties of the labor market can aid identification. For example, the relative strength of the effect on hiring as compared to separations can help distinguish between the news causing outcomes and outcomes causing the news; this will be discussed during the next section.

The use of employment data as an outcome variable might raise several concerns. First, we might be worried that only a small fraction of the individuals exposed to pessimistic news are in a position to make hiring or firing decisions. Second, we might be worried that business owners do not live (and therefore, do not subscribe to the news) in the same county in which their business resides. If a given county receives a shock of bad news, but all readers in that county own businesses in an adjacent county (leading to job losses only in the adjacent county), we would have trouble identifying the relationship between the two.

Thankfully, neither of these concerns are serious. For one, although business owners might sometimes commute to another county for work, there's no reason to believe that this effect is systematically related to our explanatory variables. Moreover, both concerns apply less to small businesses. For smaller firms, we would expect a relatively higher fraction of individuals to participate in the hiring and firing process. We would also expect higher correlation between where decision makers live and where they work. 98% of all business in the U.S. have less than one hundred employees and these firms account for a quarter of all employment; it's likely that any employment effect we observe is disproportionately driven by these businesses.

Other Data Annual county-level data on population and demographics were collected from the National Cancer Institute, while information on education attainment was obtained from the FDA. Annual county level household incomes were obtained from the BEA; unfortunately, no measures of GDP are available at this level. Finally, data on internet searches for the word "recession", to be used in the discussion section, were obtained through Google Trends.

3.4 Identification

Having constructed a county-level measure of pessimistic news, we turn to estimating the causal effect of that news on macroeconomic outcomes. Let's begin by considering an simple OLS regression of APP on a measure of labor market performance, say, total employment rates:

$$Jobs_{it} = c + \beta APP_{it} + \gamma \mathbf{X}_{it} + \varepsilon_{it} \tag{1}$$

Here, APP_{it} is the articles per person measure constructed above, $\mathbf{X}_{it}$ is a vector of observed covariates, and $Jobs_{it}$ represents the labor market variable of interest. Beta is the parameter to be estimated, and as usual, any variation in $Jobs_{it}$ unexplained by our observables is represented in the error term ε_{it}. As with all OLS specifications, correlation between articles per person and this error will bias our estimates. This could occur if we omit a variable correlated with both APP and employment, or if APP itself is correlated with employment.

To gauge the likelihood of either form of endogeneity, it's useful to express APP as the product of three separate components. To see how, note that APP is defined as follows:[5]

$$APP_{it} = \frac{1}{Population_{it}} \left[\sum_{j\ sources} (Subscribers_{j,it}) \, (Articles_{j,t}) \right]$$

We rewrite this expression by factoring the total number of subscribers in each county out of the sum:

$$\begin{aligned} APP_{it} &= \frac{Subcribers_{it}}{Population_{it}} \sum_{j\ sources} \left(\frac{Subscribers_{j,it}}{Subcribers_{it}} \right) (Articles_{j,t}) \\ &= (PenRate_{it}) \sum_{j\ sources} (SubShare_{j,it}) \, (Articles_{j,t}) \end{aligned} \tag{2}$$

I'll frequently be referring to these three components, so let me describe each in turn. The term on the left represents the total number of subscriptions to any newspaper divided by the county's population; I call this quantity the newspaper penetration rate. Since an individual can subscribe to multiple papers, or multiple editions of the same paper, this figure is an upper bound for the percentage of people in a county who subscribe to any newspaper at all.

The second term, $SubShare_{j,it}$, describes the share of a given newspaper in the total number of subscriptions; in other words, it represents the relative popularity of each source. For counties in which only one newspaper sees significant circulation (roughly 35% of counties in my sample), this term is equal to one.

The last term, $Articles_{j,t}$, describes the number of articles printed by each newspaper in a given quarter. Notice that this variable lacks an "i" subscript, this reflects the fact that newspapers do not print different editions of their paper for different counties. However, because many of the newspapers in my sample are highly local, the j and i index are highly confounded. For example, it's likely that the number of pessimistic articles printed by the Omaha World-Herald is highly sensitive to economic conditions in a few particular counties, namely, the counties near Omaha, Nebraska. In contrast, a nationally read newspaper such as the New York Times is less likely to be sensitive to employment conditions in any particular region[6]. It's the relationship between local coverage and local conditions which most threatens our estimation procedure.

In many of the empirical specifications below, I also refer to a related measure: the number of articles per reader (APR). This quantity divides the total flow of articles by the number of *subscribers* rather than the county's population. APR more closely

[5] For simplicity, I omit the summation over editions of the same paper; all of the arguments below still hold with this change.
[6] Although even in this case, we would expect the N.Y. Times to be more sensitive events in New York

	Newspaper Penetration Rate	Relative Popularity of Sources	Articles Per Source
Simultaneity	Local unemployment is negatively correlated with total subscriptions, probably due to savings behavior.	Unlikely that unemployment itself significantly shifts relative popularity of sources.	Since newspapers are highly regional, local unemployment patterns are positively correlated with pessimistic articles.
Omitted Variables	Factors such as population density or demographics might jointly affect newspaper penetration and employment.	Factors such as political alignment or education may jointly affect the relative popularity of various newspapers and employment.	Any other economic factor, say, stock market performance, might jointly affect newspapers' coverage and employment.

Table 2: Summary of possible identification issues

resembles the actual number of articles an individual reader will encounter, but doesn't take into account the share of those readers in the total population.

$$APR_{it} = \frac{1}{Subscribers_{it}} \left[\sum_{j\ sources} (Subscribers_{j,it}) \, (Articles_{j,t}) \right]$$

$$APR_{it} = \sum_{j\ sources} (SubShare_{j,it}) \, (Articles_{j,t})$$

If APR is decomposed in the same way as APP above, the result will lack the newspaper penetration term. We will use APR when we are concerned that omitted variables might jointly affect bulk subscribership to newspapers (for example, urban areas might have more jobs and more subscribers), but not the relative popularity of each source.

The key to our identification is that we will deal piece-wise with each of the three terms in equation 2. If any term is correlated with our error, due to either simultaneity through an omitted variable, we will introduce a solution for that term. After all of these treatments, none of these three components will co-vary with the error and their product APP will be exogenous as well.

Table 2 summarizes the problems facing each term by giving an example of why that term might be endogenous. For example, column two indicates that while employment is unlikely to be related to the relative popularity of different newspapers directly, the two may be jointly determined by the political alignment of a given county. Perhaps liberal counties read more optimistic newspapers and are also more willing to hire. This table is not meant to be an exhaustive list of all possible confounding factors, but rather, gives an example of the kinds of variables which need concern us. The remainder of this section will explain how to deal with each cell in this table.

3.4.1 Dealing with Simultaneity

Since the very notion of media-feedback implies both backward and forward causation, simultaneity posses an identification challenge. How do we distinguish between the news causing outcomes and outcomes causing the news? The answer is to focus on the *kinds* of news stories which are unlikely to be generated by local employment events. For example, consider the following set of headlines:

> "County jobless rate inches up: discouraged workers' re-entering the work force could account for the slight rise to 10.9 percent"
>
> "Shortfall expected by city yet again: the discrepancy could be $35 million. Leaders vow to save services and jobs"

"Brunswick to close four plants, cut 2,700 jobs to save $300 mil.; economic downturn cited in heavy reductions"

Contrast these with the following:

"Bush ousts treasury secretary, adviser; slack economy key factor"

"Economy Shrinks With Consumers Leading the Way"

"Fed chief spreads gloom; stocks boomerang downward after Bernanke predicts greater slowdown"

All of these headlines are taken from the set of newspaper articles used to construct the APP measure. The former set suffers from the simultaneity problem, these articles are obviously generated by local employment conditions. The second set, though, refers to broad economic events which affect the whole county and are less to be linked with job losses in any particular locale.The idea that pessimistic *national* news should affect local economic conditions without *being* affected by those conditions the key to our identification strategy.[7]

Looking at equation 2, though, we see that simultaneity will be a problem if $Jobs_{it}$ co-varies with *any* of the terms entering into APP. The issue discussed in the last paragraph deals with the final component of this expression, the number of articles printed by a given source in a given quarter.

$$APP_{it} = (PenRate_{it}) \sum_{j\ sources} (SubShare_{j,it})\,(Articles_{j,t})$$

Do the first two terms pose a problem? For the second term, the answer is no. There's no reason to believe that changes in employment conditions will shift the *relative popularity* of each news source. As for the first term, $Jobs_{it}$ and the newspaper penetration rate do co-vary, but the sign of this relationship favors our estimation. To see why, note that employment should affect newspaper penetration, but not vice-versa; therefore, an appropriately controlled OLS regression should identify the effect of employment on newspaper penetration. Table 21 (appendix) shows such an estimation; here, the effect of employment is regressed on newspaper penetration with county, state-by-quarter fixed effects, and a number of demographic controls are imposed. We find that employment has a positive effect on penetration, likely due the to the income effect. This means that all else being equal, counties experiencing *more* unemployment receive *less* bad news. If we nonetheless find a negative effect of news on employment, this finding would be an underestimate. Alternatively, articles per reader can be used instead of articles per person, eliminating the relevance of newspaper penetration entirely.

Turning back to the relationship between local employment and the volume of articles (the third term), I've argued that stories pertaining to national economic conditions are less likely to be related to $Jobs_{it}$. I now describe how to identify such articles in the set of pessimistic stories.

Identifying "Simultaneous" Articles The Lexis-Nexis dataset includes a number of predefined keywords and corresponding relevancy scores which assess the topic of an article. Unfortunately, not all articles have relevancy tags (this is related to when the article was entered into the Lexis Nexis system), and what's more, Lexis-Nexis only reports the top three tags. For example, if an article is tagged as "petroleum (95%)", "energy independence (90%)", and "recession (85%)", the tag "layoffs (80%)" will be omitted even though it's relevancy score is high. Nonetheless, these keywords represent a good starting point - being tagged with either "layoffs" or "local & regional" in the dataset is a sufficient (but not necessary) condition for that article being problematic.

Textual analysis was then preformed to identify problematic articles in the remaining stories. First, a word count was preformed on the titles of all articles tagged with "layoffs". The forty most commonly used words in this set of articles was identified, and number of times each of these words appears in all articles was counted. Then, a probit was run to assess how the appearance of

[7] Of course, the overall economic condition of the U.S. is the average of countless local conditions; however, the impact of any single county on the whole is very marginal. There are rare instances in which the condition of a particular county might be considered exceptionally representative of the U.S. as a whole, either for economic reasons - as in the case of New York City, or for symbolic reasons, as in the case of Detroit. However, we can get around this issue by simply excluding these areas from our analysis, either one-by-one, or by excluding all urban areas. The later is done in the results section.

each of these forty words affect the likelihood that an article was tagged with “layoffs”. Then, the probability that any article *should* have been tagged with “layoffs” was computed, based the words appearing in that story’s title and the probit scores associated with those words. This process was repeated for articles tagged with “regional & local”. Finally, articles all rated with a tag-probability above the 75th percentile for either “layoffs” or “local & regional” were dropped from the count of pessimistic articles. The analysis was repeated using the 60th and 90th percentile with little change in the subsequent empirics.

Using Only National Papers One could argue that the above procedure is only a partial solution. This is because newspapers’ coverage of even the national economy may be affected by regional conditions. For example, suppose that local layoffs make local reporters *more aware* of the deteriorating state of the entire economy. We would expect these reporters to begin writing more stories about the national economy, once again causing simultaneity between $Jobs_{it}$ and the article-count.

To deal with this issue, I can use articles only from newspapers with national circulation to construct the APP measure. The New York Times, the Wall Street Journal, and USA Today are the three papers in my sample which are circulated nationally. Since these publications report on conditions across the United States, they are unlikely to suffer from the problem above; we wouldn’t expect N.Y. Times reporters to begin noticing a downturn only after layoffs in a particular locale. The only exceptions to this line of reasoning are the home bases of each paper itself (New York City for the Times and the WSJ, Washington D.C. for USA Today), and areas considered particularly symbolic of the nation’s economic condition such as Detroit or Silicon Valley. These areas can simply be excluded from the regression; in fact, table 19 in the results section deals with this problem by dropping all urban areas from the specification.

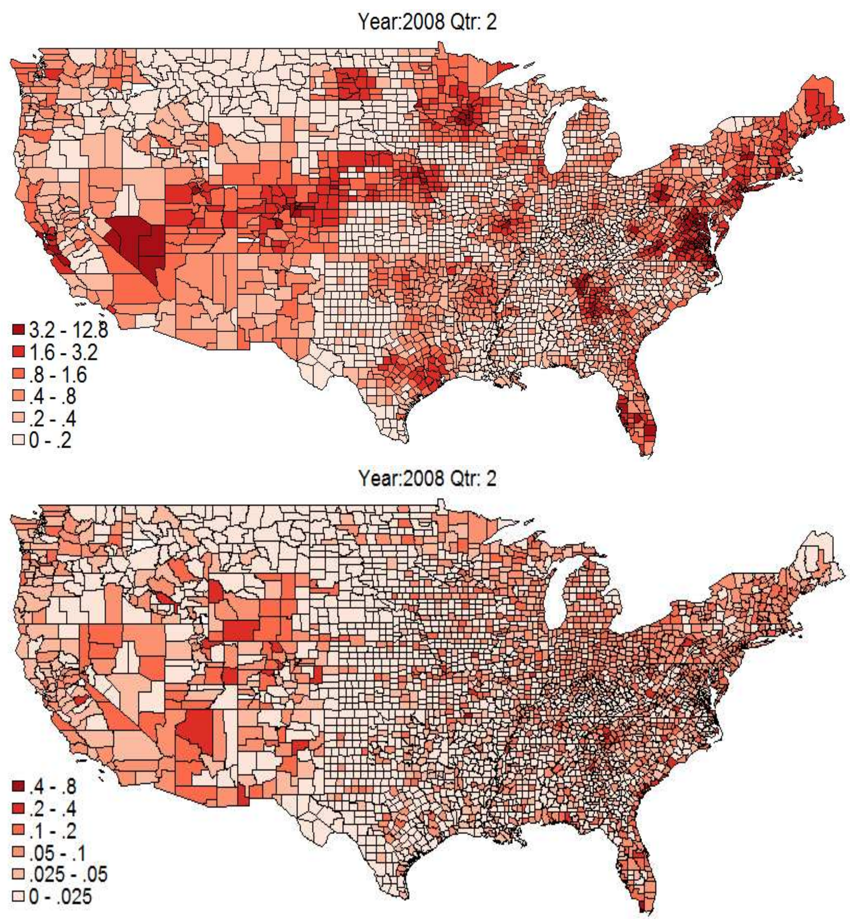


Figure 6: Dealing with simultaneity. APP computed using all articles and newspapers (top), compared with using filtered articles and national newspapers only (bottom).

Details about the estimates In addition, important details of the estimates suggest that simultaneity isn't a major problem. First, in almost all specifications, hiring shows a greater and more precisely estimated effect than separations. If our results were driven by the media reporting on employment conditions, the opposite would be true, since layoffs generate more bad press than a firm simply not hiring workers. Similarly, we can estimate the effects of APP on job losses in particular industries; if our results are driven by simultaneity, we would expect a correlation between the estimated size of the media effect and the newsworthiness of an industry. Both of these comparisons will be discussed in the results section below.

3.4.2 Dealing with Omitted Variables

Unobserved factors co-varying with both APP_{it} and labor market conditions will bias our estimation. Since so many variables could conceivably meet this criterion, dealing with this problem has been a major stumbling block of previous research. The table below displays the correlation of four measures of media pessimism with a number of county-level traits. There are two things to learn from this table. First, all of our measures of media pessimism are somewhat correlated observables, such as education or population density. Second, the per-reader measures are significantly less correlated than their per-person counterparts, implying that much of the correlation between media-pessimism and these observables is driven by the newspaper penetration rate.

To address these issues, we introduce county, quarter, and state-by-quarter fixed effects into our specification. Though the use of fixed effects is extremely commonplace in panel data analysis, I argue this technique is particularly helpful in our case because of the way APP is constructed. To see why, we note that the error term in equation 1 contains county-specific and quarter-specific components. For example, θ_i might represent a geographic variable which is absent in our model. This variable would affect employment, but it's effect is constant over time for any given county.

$$Jobs_{it} = c + \beta APR_{it} + \gamma \mathbf{X}_{it} + \theta_i + \theta_t + \theta_{i,t}$$

Recall that articles per person can be written as the product of three components: the newspaper penetration rate, the relative popularity of each source, and the number of pessimistic articles per source:

$$APP_{it} = (PenRate_{it}) \sum_{j\ sources} (SubShare_{j,it})\,(Articles_{j,t})$$

It's likely that the penetration rate, is largely determined by county level trails θ_i. The average deviation of this variable from it's across-time mean in each county is only 4%, while the mean deviation between counties in the same period is over 13%. This suggests that the variation in penetration is largely cross-sectional in nature. To the extent that this is true, county-level fixed effects will control for endogeneity though this term. Alternatively, we can use the article per reader measure, which simply does away with this first term altogether.

Similarly, the number of articles printed by each source is likely to covary only with quarterly variables, especially after eliminating articles referring to local conditions and using only national newspapers. After all, there's no reason believe why an unobserved trait particular to any given county should affect the number of stories printed by the N.Y. Times about national economic conditions.

Single Source Counties The term in the middle, the relative popularity of various sources, is the most problematic. We might expect this term to be determined by various demographic, political, or socioeconomic factors in each county. It's possible that in most areas, these variables change slowly enough to be absorbed by the county fixed effects; however, there's always the chance that a rapidly changing trait relevant to employment could also shift the popularity of a particular paper.

To mitigate this issue, it's possible to run our regression on counties which are dominated by a single news source. In such single source counties, the middle term in our definition of APP reduces to one.

$$J = 1 \Rightarrow APP_{it} = (PenRate_{it})\,(Articles_{j,t})$$

Table 3: Cross-correlation table

Variables	Art. Per Person	APP, Filtered, Natl.	Art. Per Reader	APR, Filtered, Natl.
Art. Per Person	1.000			
APP, Filtered, Natl.	0.470	1.000		
Art. Per Reader	0.745	0.346	1.000	
APR, Filtered, Natl.	0.153	0.518	0.443	1.000
Employment Rate	0.176	0.337	0.047	0.121
Population	0.128	0.155	0.054	0.029
Pop. Density	0.158	0.191	0.086	0.057
Newspaper Penetration	0.251	0.263	-0.090	-0.123
Med. Income	0.224	0.212	0.094	0.042
% College	0.283	0.312	0.118	0.071
Pct. Hispanic	0.018	-0.011	0.022	-0.011
Pct. Black	0.020	0.042	0.047	0.042
Pct. White	-0.031	-0.040	-0.062	-0.040
Pct. Asian	0.149	0.148	0.072	0.0340

In roughly a third of the counties of my sample, more than 85% of individuals subscribe to the same news source. In the results section, I repeat my analysis using these counties only and find few differences from the overall pattern.

Other Checks Finally, we impose three additional checks. First, all of the empirical results to follow are robust not only to county and quarter fixed effects, but county and state-by-quarter fixed effects. In these specifications, the effects of news on outcomes are identified by comparing counties within the same state and quarter. A number of additional factors, say, time-varying sectoral composition, should be taken care of in this specification. Second, I introduce a battery of demographic controls, such as income, ethnicity, and education. These are largely aimed at the first two terms in equation 2. Third, I include interactions between sectoral composition and national GDP. While sectoral composition itself should be absorbed by the county dummies, it could be argued that the *product* of sectoral composition and output is the relevant variable. For example, a county with many construction workers might shed more jobs in response to same contraction in output as compared to a county in which most people work in health care.

Summarizing Identification Solutions

In the preceding section, I've argued that by breaking APP into its component terms - the penetration rate, relative popularity, and articles per quarter, we can understand which factors affecting media pessimism are likely to be endogenous. Each of these terms raises somewhat different identification issues, and I've laid how to deal with each in turn. The following table summarizes the identification solutions described above.

	Newspaper Penetration Rate	Relative Popularity of Sources	Articles Per Source
Simultaneity	Correlation between jobs and penetration rate biases beta towards zero; estimated parameter is lower bound. Or, use articles per reader.	Unlikely that unemployment shifts relative popularity of news-sources.	Drop all articles pertaining to employment or local conditions. Use only articles from nationally circulated newspapers.
Omitted Variables	County and state-by-quarter fixed effects, demographic controls. Use articles per reader.	County and state-by-quarter fixed effects, demographic controls. Use only single-source counties.	County and state-by-time fixed effects, demographic controls. Use only articles from nationally circulated papers.

Table 4: Summary of Solutions for the Identification Issues Listed in Table 2

4 Results

4.1 The Delivery of Bad Economic News over the Business Cycle

As this is the first paper to measure the flow of pessimistic economic news at sub-national levels, I will begin by characterizing this flow in detail. These findings depict the media's unfolding response to the economic downturn, and will set the stage for the regression analysis that follows. Unsurprisingly, the level of pessimistic news delivered to U.S. counties is highly anti-cyclical. For example, the median level of pessimism preceding the 2008-2010 recession was close to zero prior to the downturn, and increased roughly twenty-five fold in the first quarter of 2008. Pessimism peaked in the first quarter of 2009, when the median county received 0.75 articles per person.

This number may seem modest, but recall that since many individuals don't subscribe to a newspaper, the level of pessimism experienced by a given reader is significantly higher than the per capita figure. Unfortunately, with readership information aggregated at the county level, it is only possible to know the total number of newspaper *subscriptions* in each county, not the total number of subscribers. The former could overstate the later if individuals subscribe to more than one newspaper or multiple editions of a single newspaper (weekday vs. Sunday). Nevertheless, we can use the number of articles per-subscription as a lower bound for the more meaningful per-reader figure. By this measure, the median level of pessimism during the great recession peaked at 3.5 articles per subscriber per quarter, or slightly more than one article per month for each reader.

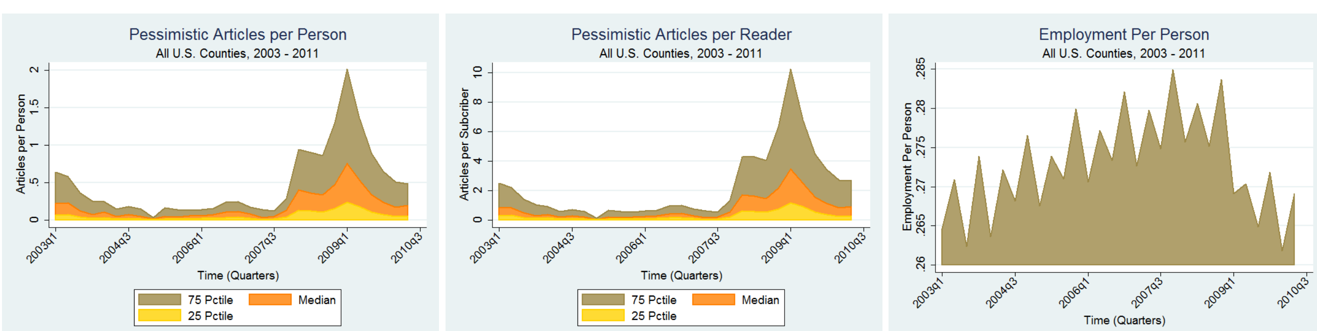
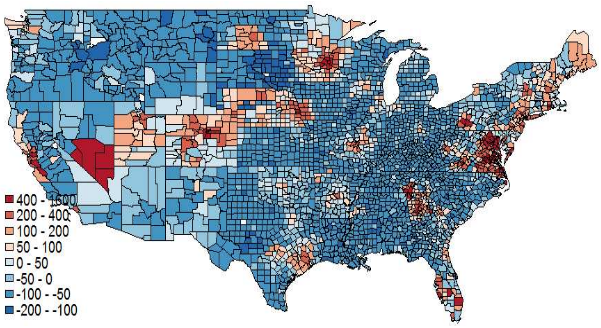
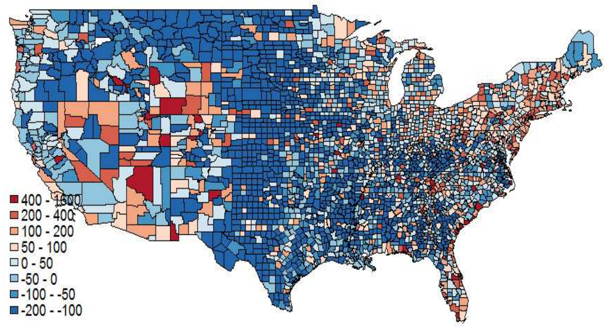


Figure 7: The Media as a Signal Booster

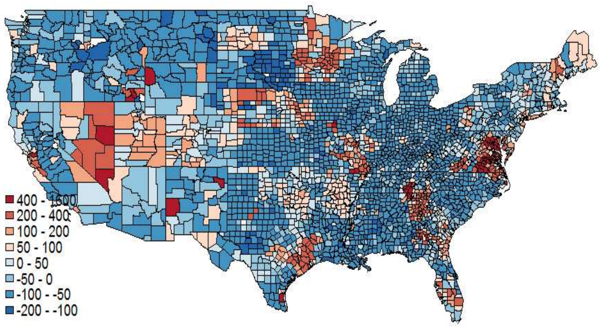
If we compare changes in media pessimism with changes in the variable of interest, unemployment, an interesting contrast emerges (figure 7). First, note that that unemployment is highly seasonal; however, this quarterly fluctuation is entirely absent in the media's response.[8] Neglecting the seasonal trend, unemployment only deviates a few percentage points from it's mean over the course of the recession; in contrast, the volume of pessimistic articles changes by more than an order of magnitude. In a sense then, the media plays the role of an economic hearing aid - it removes noise by clearing away the messy seasonal trend while amplifying volume, boosting relatively modest changes in economic fundamentals into large fluctuations in the number of articles.



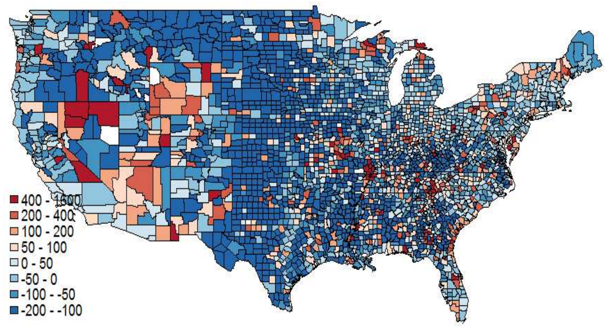
Articles Per Person, Total



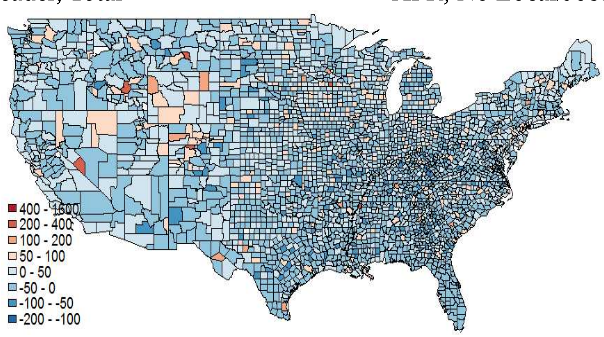
APP, No Local/Jobs, National Papers Only



Articles Per Reader, Total



APR, No Local/Jobs, National Papers Only



Unemployment

Figure 8: Cross-sectional Variation in Bad News Delivered. The top four panels depict the *percent deviation from the national mean* in the second quarter of 2008 for various measures of media pessimism. All measures exhibit far greater dispersion than employment, which typically varies by only a few percent across counties.

Cross-Sectional Variation Perhaps the media's responsiveness to the economic downturn shouldn't surprise us - after all, recessions are highly newsworthy. What's more unexpected is the degree of variation in media pessimism across counties *during the same quarter*. Figure 8 displays the volume of pessimistic articles for each county in the second quarter of 2008, compared to the

[8] Note that the median employment rate displayed in this graph is only around 30%, while the employment to population ratio for the US, as reported by the BLS, is nearly 60%. This discrepancy exists for three reasons. First, the QWI misses some forms of employment, particularly in the public sector. For example, in the year 2010, total U.S. non-farm payroll employment was measured at roughly 130,000,000, while the QWI reports only 100,000,000 employed persons for the same year. In addition, the population figure used by the BLS is the number of individuals over age sixteen, whereas the total population regardless of age is used in the diagram above. Finally, the median rate of employment across counties understates the national rate, since counties with large populations tend to have a higher employment rate.

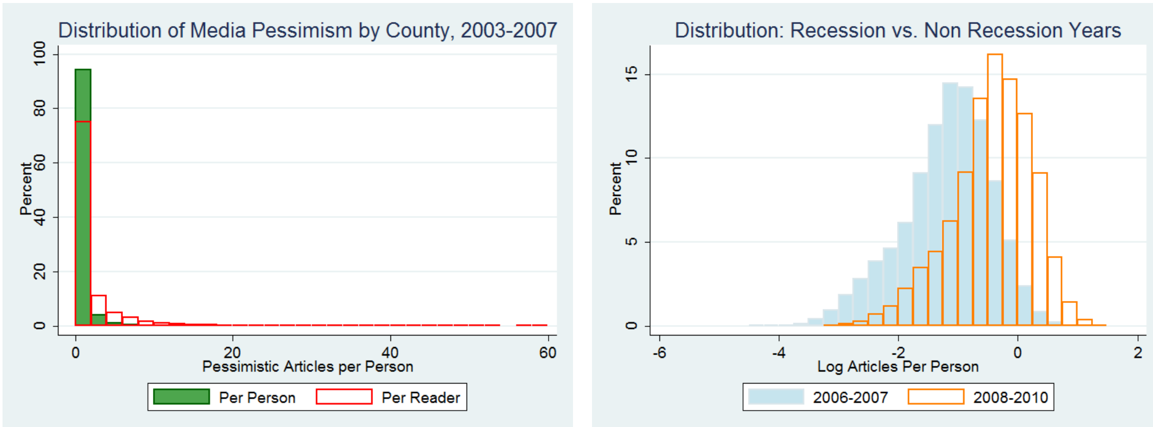


Figure 9: Cross-sectional Distribution of Bad News Delivered. Note the power-law distribution of both APP and APR, implying that the cross-county dispersion isn't merely driven by differences in newspaper penetration. Also note while the distribution shifts considerably during a recession, the variance remains pronouced.

national mean in that quarter. Various ways to measure pessimism are included; the column on the left displays the total article count, both per person and per reader; the column on the left excludes articles about employment or local conditions and counts only articles appearing in national papers. Note that even the delivery of *national* news by *national* papers exhibits widespread geographic variation. All of these measures exhibit far greater dispersion than unemployment, shown on the bottom panel.

Figure 9 displays this pattern more generally by plotting the overall distribution of articles per person, both before and during the past recession. This distribution is roughly exponential with an extremely long right tail, indicating that a small number of counties are receiving a disproportionally pessimistic media signal. This effect is *not* simply due to some counties possessing a higher rate of newspaper penetration, since the articles-per-reader measure exhibits the same pattern. Instead, it's due to the fact that a small number of counties happen to subscribe to the most pessimistic sources, while others hear a more balanced blend of media coverage.

Changes Over Time Figures 10 and 11 depict the evolution of media pessimism during the early stages of the recession. Figure 10 plots raw articles per person, with the level on the left and the percent difference from the previous quarter on the right, while figure 11 repeats this analysis but filters to remove local and job related articles and uses only articles from national sources. The take away from these pictures is that while average pessimism increases sharply over the first three quarters of the recession, the nature of this increase is highly non-uniform. This is particularly true when using only data from national papers, as idiosyncrasies in subscription to such papers ensure that certain regions receive large shocks of pessimistic news while nearby regions experience little or no increase.

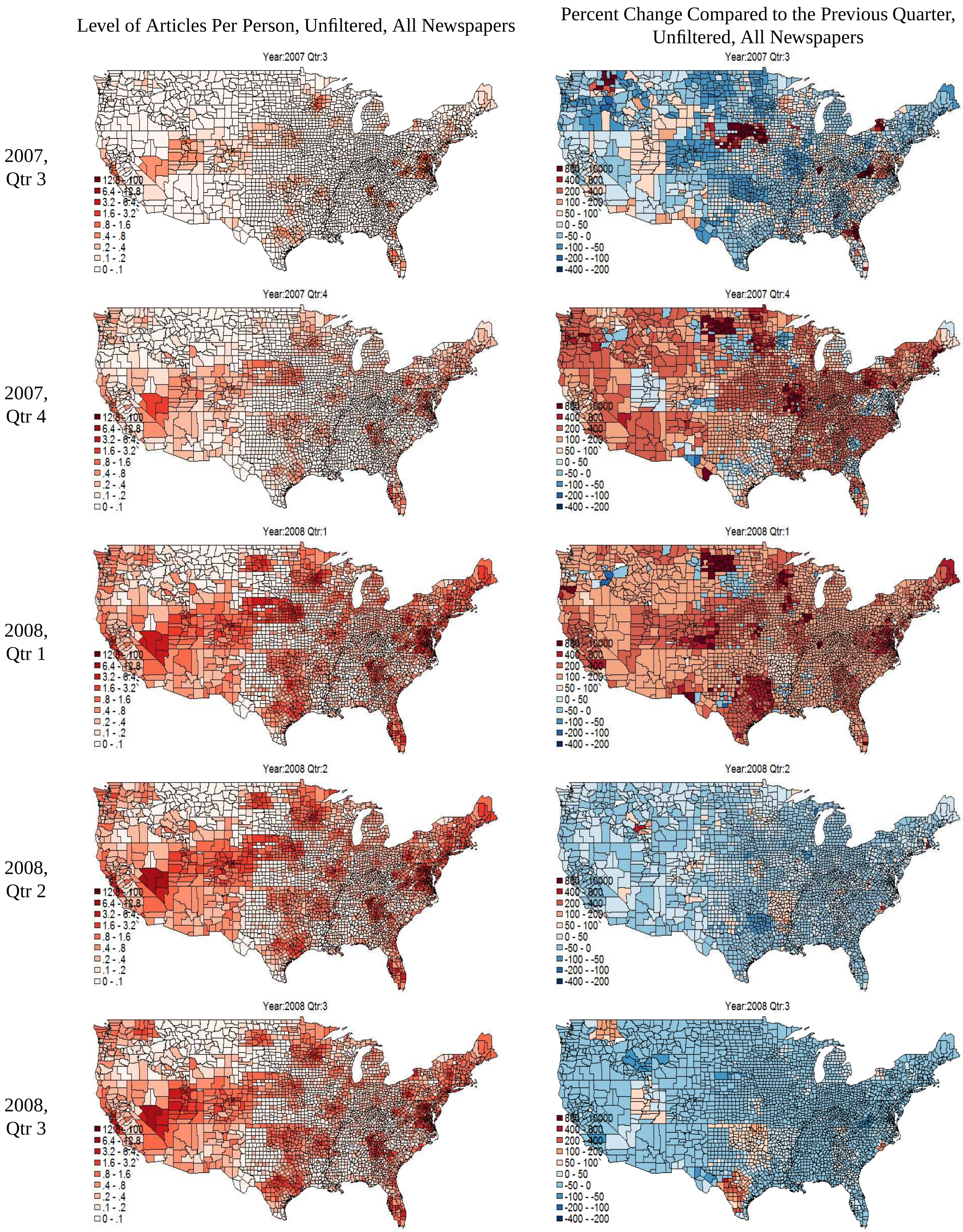


Figure 10: Pessimism in the Past Recession

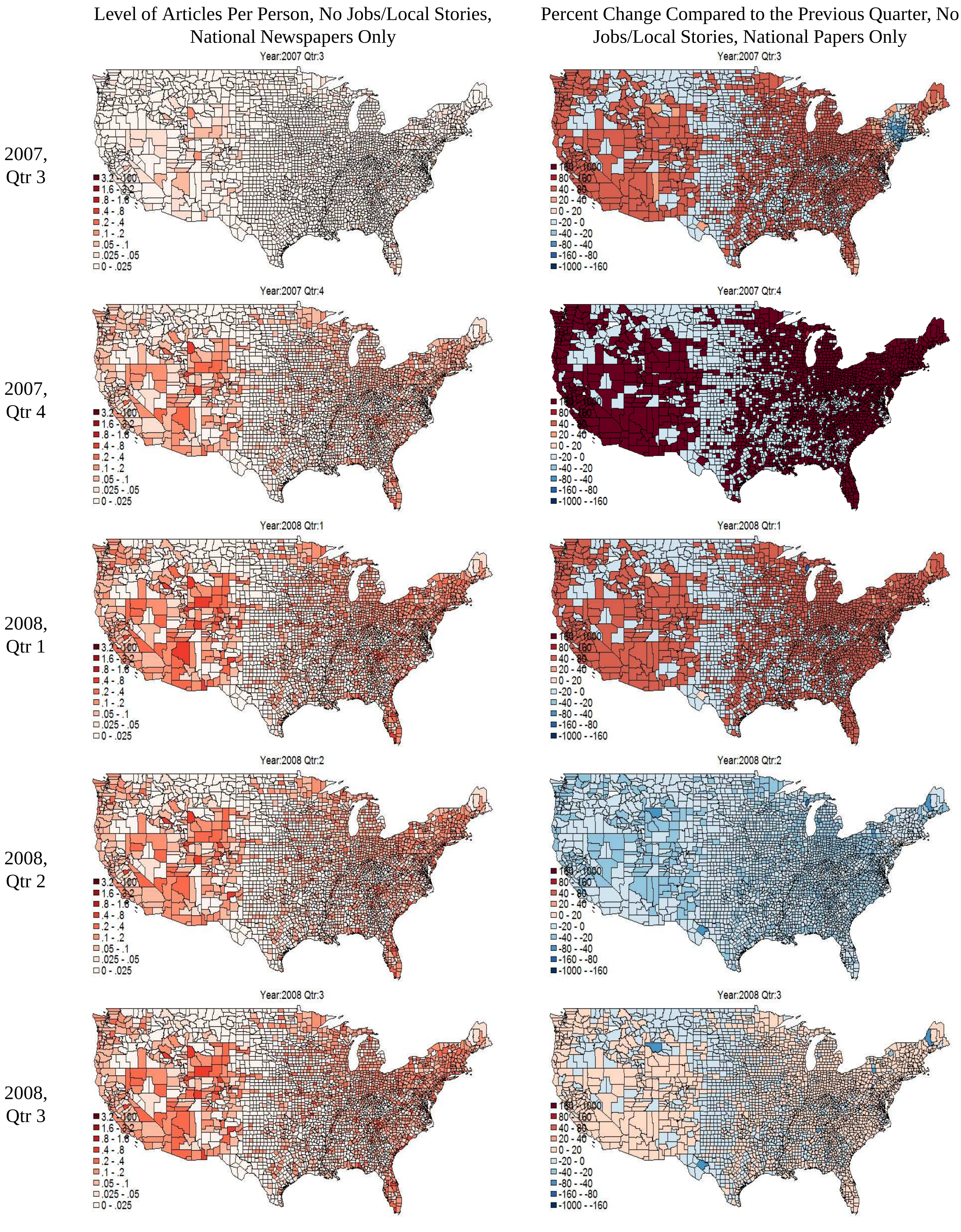


Figure 11: Pessimism in the Past Recession

4.2 The Causal Effect of Media Pessimism on Labor Market Outcomes

Having described the flow of pessimism across the U.S. over the past recession, we turn to estimating the effects of this flow on labor market outcomes. Table 2 displays summary statistics for each measure of media pessimism and number of covariates to be included in the regressions; these figures are tabulated to aid interpretation of the results below. For more details about all of the specifications please see section 3.4 which discusses identification in detail. Note that for ease of reading, all the regression tables are located in section 8, rather than inter-spaced within the descriptions below.

Effects of News on Total Employment Tables **??** and 8 shows employment regressed on articles per person and articles per reader respectively, with each column representing an increasingly rigorous specification. The dependent variable in these regressions is the log of total employment per person[9], as measured by the BLS's quarterly workforce indicators. Column one displays estimates using ordinary least squares, controlling for the demographic characteristics listed in table **??**. The OLS point estimate will be biased if any uncontrolled variable jointly affects APP and employment. As explained in section 3, the introduction of county and quarter fixed effects can help us cope with this issue by controlling for any confounds whose effects are constant in space or time; column two incorporates these fixed effects. The first lag of APP is also included in all specifications, since changes in the volume of pessimistic news may take some time to effect employment patterns. Here, articles per person is found to have a negative effect on employment at the 5% significance level, while the corresponding per-reader figure was insignificant.

Column three implements content analysis to filter out articles referring to either employment or local conditions; the details of this procedure are described in section 3. Column four repeats the same regression, but introduces county and *state-by-quarter* fixed effects. In this specification, the impact of pessimistic news on employment is identified from variation between different counties in the same state and quarter. Here, both APP and APR are found to negatively affect employment, with the per-reader figure remaining robust to state-by-quarter dummies.

Columns five and six maintain the filtering of articles, but only uses articles from the three sources in my sample with national circulation: the New York Times, the Wall Street Journal, and USA Today. As mentioned in the identification section, we expect these national papers to be even less sensitive to local employment conditions in any given county. Here again we find negative estimates, with the per-reader figure significant to five percent even with county and state-by-quarter fixed effects imposed.

Job Creation and Destruction The jobs data released in the QWI are highly detailed and contains separate measures for hiring and separations. Tables 9 though 12 display regressions analogous to the results above but with job creation and destruction on the left hand side. The pattern of results for hiring is similar to those for employment, with a number of exceptions. First, virtually all of the results are now significant to the more rigorous state-by-quarter fixed effect. Second, the absolute magnitude of the effects are much larger, particularly when using articles from only national sources. For separations, the effects are more ambiguous. Most specifications, particularly the more rigorous ones, find a positive but insignificant contemporaneous effect. In contrast, the lagged effects appear to be consistently negative and are significant in some specifications.

The clear take away from these tables is that the effect of pessimistic news on employment appears to be driven by changes in hiring rather than separations. In fact, pessimistic news in the previous quarter appears to suppress job destruction rather than promoting it. Interestingly, these results are results are consistent with recent findings in the empirical literature on labor market dynamics. While traditional models of employment have emphasized the role of separations in driving countercyclical employment, new studies imply that the job-finding rate is instead the key player (Shimer, 2007; Yashiv, 2006; Hall, 2005). For example, Hall (2005) finds that while involuntary separations increased during the 2001-2003 recession, this effect was nearly canceled out by a sharp reduction in the quit rate. Overall, separations during the recession remained nearly constant, with fluctuations in the total unemployment driven almost entirely by changes in job-finding.

Importantly, this asymmetric effect of bad news on hiring and separations also argues that simultaneity isn't biasing our results. This is because layoffs are much more newsworthy than a simple lack of hiring - between 2008 and 2010, articles mentioning layoffs outnumbered articles mentioning hiring by more than a factor of three to one in the Lexis Nexis Database. If our results are driven by newspapers covering local job losses, we would expect the coefficient on separations to have a large, positive and statistically significant point estimate, with a much weaker effect on hiring. This is the opposite of what we find.

Changes in Effect Size over the Business Cycle Do the size of our estimates change over the course of the past recession? There are a number of reasons to believe that this might occur. For example, suppose that workers possess heterogeneous productivity, and that the least productive workers are laid off at the beginning of the recession. The remaining more productive workers then face a

[9] Almost all of the results to be discussed also hold in levels with a higher level of significance. However, normality testing of the residuals suggested that using a logged dependent variable is more appropriate for these specifications

lower probability of being terminated, regardless of how much bad news is printed. Recent theoretical papers have considered this possibility (Villena-Roldan, 2010). Alternatively, imagine that the areas receiving a disproportionate quantity of bad news over-react by drastically cutting hiring. In subsequent quarters, job creation could rebound as employers in those counties recognize that the news shock they received was spurious.

Tables 13 through 15 break down the effects on both job creation and job destruction over the course of the recession, and show some signs of this pattern. For example, while the point estimates for hiring and employment remain negative between 2007 and 2009, they diminish in precision; the estimate in 2010 is actually positive but insignificant. Separations also show an interesting trend, with a positive (albeit insignificant) sign in 2007 and reversing in subsequent years. It's possible that pessimistic news does lead to layoffs in the early stages of the recession, with the suppression of voluntary separations kicking in later in the cycle.

Tables 13 though 15 are also a first-pass at addressing a question which we haven't yet asked. This question can be levied against any theory which invokes a feedback mechanism to explain business cycle fluctuations: namely, what makes the feedback stop? After all, if bad news begets unemployment, and unemployment begets bad news, wouldn't the economy worsen indefinitely? One possible answer is that agent's reactions to bad news exhibit some kind of diminishing returns. It's not unreasonable to assume that once the airwaves become saturated with dire headlines, additional pessimistic information becomes relatively inconsequential.

Another possibility is that economic fundamentals intervene. For example, a car dealer might fear that spooked customers will stop buying cars (and reduce his labor force accordingly), but only up to a point: cars go out of service at a certain rate, there is always *some* demand for new automobiles. These facts about supply and demand cannot be disputed no matter how pessimistic the news, and may serve to break the feedback cycle once the economy is pushed beyond a certain point. Whatever the reason, our results are consistent with the idea that pessimism makes the greatest impact the beginning of a downturn, with the coefficients on separations and hiring reversing in sign and diminishing in precision as the recession drags on.

Cross-Industry Comparison Table 16 presents the effect on employment for level-two NAICS industries, using the most rigorous specification in table **??**. These estimates are useful not only because they reveal differences in each industry's response to media pessimism, but because this heterogeneity can again be used to rule out reverse-causation. If we believe that our results are driven by pessimistic news dampening employment, we would interpret a larger coefficient in this table as an industry which is more sensitive to bad economic news. If we instead believe that these results are driven by losses in employment generating media coverage, then the *reciprocals* of this coefficient would represent the number of articles per person generated by the loss of one job. In other words, these reciprocals would represent the relative news-worthiness of job losses in a given industry.

$$Jobs_{it} = \beta APP_{it} + other\, terms$$

$$APP_{it} = \frac{1}{\beta} Jobs_{it} + other\, terms$$

The third column in table 16 displays these reciprocated coefficients, while column 4 displays an independent measure of news-worth. This measure was computed by dividing total job losses in a given industry against the number of newspaper articles in the Lexis Nexis database describing layoffs in that industry. If we believe that reverse causality is a problem in our estimation, we would expect the quantities in these two columns to be positively correlated in absolute value. In fact, we find that they exhibit a weak negative correlation (-0.19). Instead, our coefficients are more correlated (albeit still weakly, with a coefficient of 0.21) with the decline in output in each industry during the recession itself. This supports the interpretation that the negative sign on our estimates is the results of industries cutting employment upon hearing negative news, in anticipation of a reduction in aggregate demand. Looking at the list of industries, we can see a qualitative agreement with this theory. Industries which are particularity cyclical, such as construction, retail trade, or accommodation exhibit large coefficients, while recession-proof industries such as agriculture or health care have positive and insignificant point estimates. This pattern of results is difficult to explain if we believe that they arise from the media's coverage of layoffs in each industry.

Additional Checks Tables 17 and 18 repeat the most rigorous specification above (Table **??**, Columns (4) and (6)) but restrict the sample to the set of counties in which more than 85% of all subscribers read the same newspaper. These counties represent areas dominated by a single print publication and represent roughly a third of all counties. As argued above, county level fixed effects will control for the influence of confounding variables so long as the newspaper subscribership pattern in each county is based on time-invariant traits. This is more likely to be true in these single-source counties, where subscribership can only vary due to *whether* an agent subscribes to a paper, not *which* paper that agent subscribes to. More formally, recall that articles per person can be written as:

$$APP_{it} = (PenRate_{it}) \sum_{j\ sources} (SubShare_{j,it})\,(Articles_{j,t})$$

For single source counties, the middle term reduces to unity.

$$J = 1 \Rightarrow APP_{it} = (PenRate_{it})\,(Articles_{j,t})$$

For articles per reader, which doesn't contain the term $PenRate_{it}$, this independent variable further reduces to the total count of pessimistic articles printed by national papers. We find here that while our results diminish in significance due to a reduction of the sample size, the per-subscriber effects remain significant. Further, the sign of the effects are all consistent with previous estimates.

Tables 19 and 20 also repeat the most rigorous regression in table **??**, but include only non-urban areas, defined as areas with a population density of less than 500 persons per square mile. As mentioned in the identification section, our use of national news in national papers assumes that these papers can be viewed as exogenous to conditions in any particular county. However, this assumption might fail for the counties in which these papers are based (New York City and Washington DC) and for locales considered symbolic of the nation's economic state, such as Detroit or silicon valley. The dropping of urbanized areas deals with both of this issues, and does not lead to significant changes in our results.

5 Discussion

The findings above can be summarized as follows:

1. The *signals* agents receive about the state of the economy the vary much more greatly in time and space the *actual* condition of the economy.

2. Pessimistic news has a negative effect on total employment and hiring, and mixed effects on separations. These effects are most prominent at the beginning of a business cycle contraction.

3. The pattern of effects - particularly the stronger results for hiring as compared to separations, and industry specific estimates, suggest that reverse causation isn't driving our results.

This paper argues that the most parsimonious interpretation of the evidence above is that exposure to pessimistic economic news can dampen labor market activity, especially new hiring. On the face of it, this claim doesn't seem very extreme. To admit that different counties will adjust their behavior when exposed to differing levels of bad news simply means that agents act on information they receive from the news media. Presumably, this is the reason many people read the news in the first place.

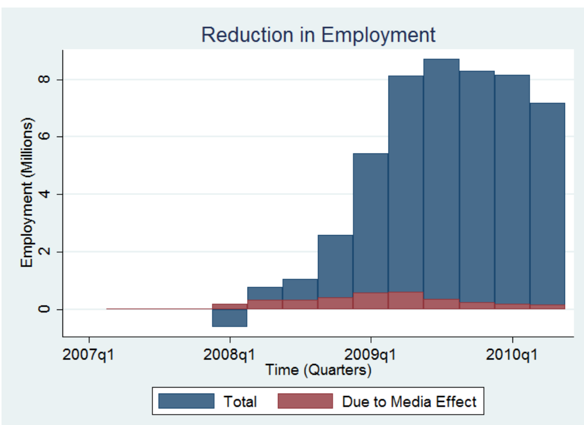
However, the detection of media-feedback raises broader questions for our understanding of the business cycle. What is the significance of the the media's effect, compared to more traditional sources of business cycle amplification? How do these results bear on related topics in macroeconomic theory, such as the existence sunspot equilibria and the Keynesian notion of animal spirits? And finally, what policy implications can be drawn from these findings? This section will discuss these questions in detail.

Quantifying the Media's Significance Is the media's impact on unemployment a secondary correction, or a significant first-order effect? This question can be approached in two ways. One is to simply predict what employment in a given county and quarter would have been *had no pessimistic news been delivered* to that county, holding constant all other covariates. The difference between this number and the same prediction using *observed* levels of news, summed across counties, would constitute the total employment effect of the media in any given period. This number can then be compared with observed changes in total employment over the course of our sample.

Figure 12 displays the results of this procedure. Here, the blue bars represent total employment in a given quarter, compared to their per-recession values in 2007 for the corresponding quarters (note that this quarter-by-quarter comparison is necessary due to the seasonality of employment). The red bars display the quantity of these job losses which is attributable to the media's influence. The figure to the right simply plots the relative size of the blue and red bars.

We can see that the reduction in employment due to media-feedback is on the order of half a million persons per quarter. The effect of the media is particularly pronounced at the beginning of the recession, and fades as the recession progresses. This pattern shouldn't be surprising given figure 7, as the spike in pessimistic articles is relatively short lasting, falling off significantly after 2009. In contrast, employment remains suppressed until the end of the sample, remaining lower than average even at the time of writing this paper.

We also need to keep in mind that these estimates tally the effects of newspaper articles only. The total impact of the media would need to incorporate all news sources, including television, radio, and the internet. Given that twice as many people get their news from TV, and roughly equal numbers get their news online (albeit, sometimes from electronic versions of popular newspapers), the total effect of the media is likely to be larger than our estimates here.



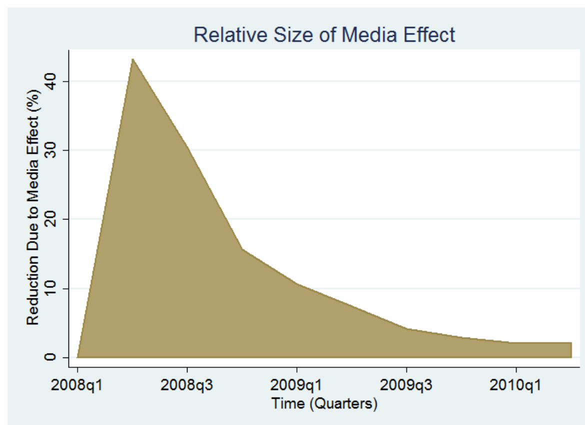


Figure 12: The relative size of the media's effect attenuates over the recession

Another way to assess the impact of the media is to find a specific economic event which generated bad press, and compare the direct impact of that event with the impact of the press that it generated. This analysis was preformed for the collapse of Lehman Brother Holdings in 2008. The first-order impact on the labor market from this event was the loss of employment for Lehman's some 26,000 workers. This event also generated an incredible amount of bad press. Taking coverage only from a two day window before and after the Lehman bankruptcy, we find some 760 news stories across 114 U.S. newspapers. In counties which subscribe to those papers, this would cause a significant increase to the flow of pessimistic news. For the average county, this single highly publicized event increased the number of pessimistic articles by more than 60% in the third quarter of 2008. This shock would have a significant effect on total employment.

For example, Autagua county Alabama received nearly a 100% shock to pessimism per capita as a result of coverage of the Lehman Brothers collapse – an increase from 0.239 to 0.443 articles per person. Using the estimates in table 6 column 4, this would have reduced employment in Autauga county by 19 persons that quarter. Nearby Dekalb county experienced a smaller increase in pessimism, from .395 to .485; however, since it has a larger population, this would have still caused a reduction in employment by some 11 jobs. Summing across the country we find the total impact on employment to be some 300,000 jobs. This is more than ten times larger than the immediate employment impact.

Of course, we have to take this kind of counterfactual estimate with a grain of salt. For one, we are assuming that the impact of a article about Lehman Brothers have the same effect as an average pessimistic article. For another, it's difficult to say how many jobs were lost in the collapse of Lehman due to conventional modes of amplification - for example, the reduction in aggregate demand resulting from the employees' lost income. However, this example highlights the potential of the mass media to affect aggregate outcomes. Even counties with no direct connection to the Lehman Brother's failure would have been affected by the pessimistic news it generated. And though the impact in each county is small, the incredible reach of the media – the impact on countless readers across the US - makes the total loss formidable.

Sunspots, Animal Spirits, and Amplification I want to connect the idea of media feedback to two notions which I've mentioned over the course of the paper, but whose definitions I haven't made explicit. The first is the notion of "sunspots". This is the idea that factors totally orthogonal to economic reality can nonetheless impact economic outcomes by altering people's beliefs. To see the connection, consider that different counties in the United States received different levels of pessimistic news at the eve of last recession. But what was the "correct" level of news for a county to receive? Whatever it was, idiosyncrasies in the way that news is delivered made sure that most county did *not* receive that level, and as a consequence experienced somewhat different labor market outcomes. In other words, the results above constitute evidence for media-driven sunspots.

But there's a more nuanced way to think about this. If we concede that counties are differentially affected by the media, we must admit the possibility that the *same* county, had it received a different level of news, would experience a different economic outcome. If we apply this to the U.S. as a whole, it would mean that events which are exogenous to the state of the economy, but which globally affect media coverage, say, competing coverage of a war, might make a business cycle fluctuation stronger or weaker. It also means that *all* recessions are somewhat worse than they would otherwise be if the media were less of a presence. This is an important point to understand - a sunspot doesn't have to be all or nothing. Rather than picturing a totally spurious shock to bad news causing a recession out of nowhere, it's more accurate think of the media as a channel of amplification. While the strength of most such channels depend on deep economic parameters (such as the elasticity of labor supply), the strength of the media's amplification depends largely on non-economic factors.

What's more, consider the fact that everyone with a mouth is, at some level, a news organization. If agents begin to hear gloomy news from the people around them, wouldn't this affect their behavior for the same reasons as reading that same news in the paper? Any mechanism which assists the spread of economic information can play this role. By this logic, the media is part of a *class* of amplification mechanisms, ones which involve the way information is shared in the economy.

Connecting the Dots - The Role of Psychology

What is the connection between media-feedback and the Keynesian notion of animal spirits? Animal spirits are psychological sunspots - agents basing their behavior not on economic fundamentals, but on subjective states such as fear or uncertainty. Above, I find that pessimistic news lowers employment largely by suppressing hiring. Presumably, this effect is mediated by business owners listening to the news and changing their beliefs about the future of the economy. Are subjective states such as fear part of this change in beliefs? It's difficult to answer this question without a measure of psychological sentiment; unfortunately, no such measures are disaggregated at the county level.

However, a viable proxy for this measure can be obtained using search data from google trends. Google collects search data at the DMA level and compiles this data into an index of how many times a particular term is searched compared to other terms. Figure 13 plots the number of times users googled the word "recession" against the University of Michigan's consumer confidence index and shows a clear anti-correlation. While not a perfect proxy, it seems reasonable to assume that most people searching for "recession" are at least concerned about the state of the economy. This variable can help us connect the dots between media sentiment, consumer sentiment, and economic outcomes.

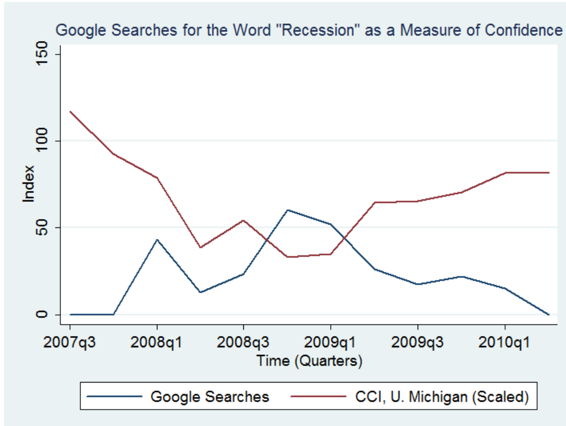


Figure 13: Median level of Google searches for the word "recession" across all counties vs. the University of Michigan's consumer confidence index

Imagine an OLS regression of google searches for the word "recession" on employment:

$$Jobs_{it} = c + \beta Searches_{it} + \gamma \mathbf{X}_{it} + \varepsilon_{it} \tag{3}$$

Estimating this equation is problematic for the same reasons that estimating jobs on news is problematic. First, unobserved factors may jointly affect the level of search queries and employment - for example, differential access to the internet. Moreover, these searches are likely to be generated by job losses themselves. One approach to overcome these issues is to identify a valid instrument for the number of google searches. This instrument must be relevant - that is, it must be correlated with the number of google searches, and it must be uncorrelated with the error term in the equation above.

In section 3.4, I argue that with fixed effects in place, and after the treatments for simultaneity (dropping articles, using only national sources), APP is uncorrelated with the error term in a regression on jobs. Note that condition is equivalent to satisfying the exclusion restriction for the specification above. In other words, if media-pessimism and google searches are correlated, then media-pessimism serves as a viable instrument for consumer sentiment as measured by google trends.

Table 5: Effects of Google Searches on Employment, Instrumented by APP

	(1) 1st Stage	(2) Tot. Emp.	(3) Hires	(4) Seps.
APP, No Local/Jobs, Natl.	20.6326***			
	(0.000)			
Google Searches		-0.0021***	-0.0068***	-0.0003
		(0.000)	(0.000)	(0.805)
Observations	47683	46642	46418	46609
Wald-F(1st Stage)		119.7930	118.5358	118.6318

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01
2. 1st stage is Google searches regressed on APP and demographic controls with county and quarter FEs.
3. 2nd stage is identical to column (5) in table 6, but with instrumented Google searches replacing APP; standard errors clustered at the county level.
4. Due to heteroskedasticity, the Kleibergen-Paap Wald F-statistic is used.

Column (1) in table 5 displays a regression of google searches for recession against APP, dropping local and employment related articles and using only national papers. Reverse causation shouldn't be a major problem here (as it's unlikely that google searches themselves cause bad news), and unobserved heterogeneity is dealt with in the same manner as above - county and quarter fixed effects and time varying demographic controls. Note that negative news has a strong positive impact on the number of searches; the Wald F-statistic in the first stage is quite large, implying that weak instruments isn't a concern.

Columns (2) through (5) displays labor market performance regressed on google searches instrumented by APP. The specification is the same as above, with county and quarter fixed effects. We see the same general pattern as the tables in the results section; precisely estimated negative effects on employment and hiring and an insignificant effect on separations. To the extent that these google searches are a valid proxy for individual sentiment, these results indicate that sentiment has a causal effect on economic outcomes as the animal spirits hypothesis would suggest.

On could argue that individuals who search for the word "recession" on google are acting rationally, rather than in fear. It might be the case that as individuals sense a deteriorating economy, they go to google seeking more information. However, remember that our instrument is the number of pessimistic articles as reported by national papers, dropping articles which pertain to local conditions or to jobs. Thus, the variation in instrumented google searches is being driven by regional variation in media coverage about the national economy. As I argued above, since there is only *one* state of the national economy, these variations in the media's volume should be viewed as orthogonal to economic fundamentals. Therefore, the variations in public sentiment that they cause should be viewed as orthogonal as well. In other words, the results above suggest that consumer sentiment sunspots, caused by media sunspots, can impact labor market outcomes.

Media-feedback and Rational Expectations Is it possible to reconcile the results above with standard DSGE models, and in particular, with the assumption of rational expectations which appears in nearly all such models? In this section, I will argue that the answer is yes, although whether such models are the *ideal* candidate to portray these effects is an open question. Recent research has shown that many DSGE model can exhibit dynamics consistent with sunspots. To derive such a model, one usually begins with a non-stochastic framework that exhibits a locally stable steady state. Such models often possess "indeterminacies" - a continuum of non-stationary solutions which converge towards (but never reach in a finite time) the steady state. In a stochastic context, it's possible to randomize across these indeterminacies to generate multiple solution paths, all of which satisfy the rational expectations assumption. Each of these rational expectations equilibria are consistent with a particular set of beliefs, beliefs which are realized in expectation if agents act on them. For a detailed example of such a model, see Farmer (1999).

This approach has the advantage of preserving the current paradigm. However, it does have a number of drawbacks. First, we need to choose a model in which these stationary equilibria occur. Sometimes this requires parametrizations which are inconsistent with empirical measurements (Herrendorf et al., 2000). Moreover, the solution is very ad hoc - the framework doesn't distinguish between sunspots arising for different reasons, nor does it explain what the size of the sunspot perturbations should be (it simply defines this size when it sets the variance of the shock u_t). In reality, these questions are answered by structural factors associated with each type of sunspot. For example, the magnitude of the media's effect might depend on the number of news organizations and their popularity, while the effects of psychological attitude might depend on behavioral parameters of agents within society, say, their level of risk aversion.

What's more, since this solution is consistent with rational expectations, it still posits that agent's predictions of the future (in expectation) were in line with what actually transpired. The data are silent on this question - while our results show that the news had an effect on economic outcomes, there's no way to know whether agents expected exactly those outcome to transpire when they acted on that news in the first place. In fact, it's very difficult to conceive of how such evidence could be obtained - did residents of a county which lost 30 jobs expect to lose that exact number? In this sense, the difficulty of falsifying the notion of rational expectations is one of its major weaknesses.

It's not the goal of this paper to judge whether media-feedback is best modeled within or without the context of rational expectations. In some ways, our choice as macroeconomists is limited because in the current generation of models, rational expectations is employed largely for the purpose of tractability. This paper merely argues that media-feedback and related phenomenon *should* be modeled, however we choose to do it. There has been a tendency to view sunspots - even sunspots within the context of rational expectations - as pathological. My hope is that the empirical evidence presented here can ease the stigma against such solutions.

Policy Implications I've argued above that the media serves as a channel of business cycle amplification, implying that recessions are worse than they would otherwise be if the news media was less of a presence. But what, if any policy implications follow from this conclusion? At first pass, it might seem like there's nothing to be done about the issue; after all, it's not as if the media could be prevented from covering negative economic events.

But in another way, the existence of the media effect *has* important implications for government policy. This is because media-feedback implies that government intervention can affect the economy in at least two ways. First, policies such as monetary expansion can directly impact economic fundamentals. For example, in traditional Neo-Keynesian models, price rigidity leads to a rise in real income when the money supply is increased, leading to gains in output and employment. But a non-zero media effect implies that *news* of intervention itself could also affect economic performance, regardless of the policy's impact on fundamentals.

This idea is not as far flung as it might sound. In a study of the European Central Bank, Berger et al. (2009) find that while real economic conditions influence reporting, "ECM communications - in particular, though it's press conference on meeting days is able to influence both the extent and the favorability of the media's coverage of it's decisions." Konstantinou and Tagkalakis (2008) find evidence that expansionary fiscal policy improves business and consumer confidence and suggest that this improvement should be viewed as as secondary goal of such interventions. This idea that the government's *media presence* can affect economic sentiment has long been recognized - even during the Great Depression, the Roosevelt administration oversaw a significant media campaign to sell the economic policies that were being put in place to fight the contraction.[10]

It has been frequently argued that in the past recession, the government did a poor job of marketing it's numerous interventions to the public. For example, a survey by Harris Interactive revealed that only 23% of Americans think that the TARP program helped the economy. In contrast, a survey of economists conducted by the University of Chicago showed that 80% of economists believed that TARP was beneficial. Treasure secretary Henry Paulson has frequently stated that while he doesn't regret bailing out the banks, he erred in failing to communicating the rationale of this move to Americans at large. Presumably, if economic agents are unconvinced that a given government program will help the economy, it will not stimulate the economy though the channel of public sentiment described above.

A more detailed analysis of this effect is beyond the scope of this paper. It may be the case that the media effect of government policy is small compared to it's impact on economic fundamentals. However, it's also the case that marketing a given policy intervention is likely to be far cheaper than the intervention itself. Perhaps a small investment in cultivating a positive media presense could pay large dividends for the government over the course of an entire recession.

[10] For example, Roosevelt's famous "fireside chats" where a series of radio messages designed to inform the public of the government's progress in combating the recession.

Part II

Uncertainty and Risk Averse Firms in DSGE

Imagine that the management at a large U.S. firm is faced with the following choice:

1. Continue making 1 million dollars (per quarter) in profits
2. Play in a lottery in which there was a 50% chance of making zero profit next quarter, and a 50% chance of making two million dollars in profit.

Consideration of this type of lottery is how microeconomists define risk aversion for individuals. Faced with the choice above over their own incomes, individuals are consistently observed to favor the first option. This paper seeks to understand the macroeconomic consequences if firms also favor the first option. In other words, it asks: how would the economy behave if firms (or their management) were risk averse in profits, just as households are risk averse in consumption?

Why does this question merit consideration? In the first place, there is broad micro-level evidence that firms do behave in a risk averse manner, evidence which I will summarize in the following pages. More importantly, the assumption that firms are risk averse leads to qualitatively different business-cycle dynamics. Risk averse firms seek to smooth profits and respond to economic uncertainty with precautionary behavior, just as households do. As I will argue in greater detail, this behavior can resolve a challenge faced by a broad class of RBC models: the difficulty of triggering an economic contraction with a Keynesian demand-side shock.

Demand Shocks

The prototypical aggregate demand shock asks us to imagine a scenario in which consumers, worried about the future of the economy, cut back on spending. As demand contracts, output and employment fall. Keynes called this scenario the "paradox of thrift"; with the economy stagnating due to collective savings behavior, government spending is needed to boost aggregate demand and halt the downturn.

In the modern DSGE paradigm, this type of scenario can be modeled in two ways. First, one can apply a direct shock to the consumer's intertemporal utility function. For example, a sudden increase in consumers' discount rate β will result in lowered consumption and increased savings. More recently, a growing literature argues that an *uncertainty* shock, an increase in the variance of a stochastic variable driving the model, will also lead to a contraction in aggregate demand. Faced with a more uncertain future, risk averse households will engage in precautionary saving, causing consumption to fall in a manner analogous to a first-moment shock.

However, it's widely understood that this type of model does not display the intuitive response. Instead, such a demand shock is usually expansionary. The reason is the equivalence between savings and investment. As households put more of their money away, investment increases, interest rates fall, and the capital stock expands. In models with an elastic supply of labor, households also engage in precautionary employment, increasing hours worked in order to further boost savings and hedge against the future. With both inputs into the production function rising in response to the shock, the economy enters a long term boom.

5.1 Approaches in the Literature

Given the conceptual desirability of demand driven recessions, numerous authors have tackled this "co-movement problem". Table 1 summarizes this literature; as whole, these papers take one of two main approaches. The first is to modify the consumer side of the problem so as to reduce the intensity of savings. For example, Yi (2006) finds that when consumers' utility function exhibits habit formation, an increase in β can lead to a reduction in investment. This is because rational households know that they will "get used to" lower consumption levels, and find it less necessary to save. While this approach can restore realistic business cycle behavior, it

	Type of Demand Shock	Ingredients Used in Model
Basu and Bundick (2012)	2nd moment shock to consumer utility 2nd moment shocks to technology	Nominal Rigidities (price only)[a] Countercyclical markups Adjustment cost (capital)
Huo and Rios-Rull (2013)	1st moment shock to consumer utility	Labor & Capital adjustment costs Search frictions (complex)[b] Variable capital utilization
Bai et al. (2012)	1st moment shock to consumer utility	Search frictions (complex)
Yi Wen (2006)	1st moment shock to consumer utility	Habit Formation Variable Capital Utilization Adjustment Costs (capital)
Bloom et al. (2012)	2nd moment shock to technology	Adjustment costs (Labor & Capital) Search frictions
Bloom (2009)	2nd moment shock to technology	Adjustment costs (Labor & Capital)[c]
Leduc & Liu (2012)	1st moment shock to consumer utility	Search Frictions Nominal Rigidities (wage and price)

[a]Their model also works under sticky wages, but these are not required to generate realistic co-movement
[b]Here, there are search frictions not only for labor, but for varieties of goods
[c]This was an earlier paper with most results holding in partial equilibrium, though the author gives a heuristic argument that they also hold in general equilibrium

Table 6: Approaches in the Literature to Resolving the the Demand Shock Co-movement Problem

weakens the notion of a demand-driven recession in the first place. After all, if consumers are not cutting back, in what sense is the recession still caused by a reduction in aggregate demand?

The alternative approach, which I employ in this paper, is to modify the firm side of model so as to decrease the *demand* for investment in response to the shock. The intuition comes from economics 101: when supply and demand curves both shift to the left, quantity will fall if the reduction in demand dominates in magnitude. For example, Basu & Bundick (2012) envision an imperfect competition framework with counter-cyclical price markups. They show that in the presence of sticky prices, households' choice to engage in precautionary employment drives up firms' markup over marginal cost. This larger markup increases the degree of monopoly power in the economy and so causes factor demand and output to fall. This reduction in demand overwhelms the supply effect in both factor markets, causing investment and employment to fall as well.

Despite this broad range of solutions, the current literature leaves much on the table. One problem is the sheer number of mechanisms necessary to trigger the recession. For example, Huo and Rios-Rull (2013) incorporate not only search frictions in both labor and goods, but two types of adjustment costs and variable capital utilization. What's more, they show that in their model, *all* of these ingredients are necessary in order to facilitate a demand driven contraction. Compared with technology shocks, which parsimoniously deliver business cycle stylized facts with little additional complexity, these workarounds to make the notion of an aggregate demand recession seem increasingly forced. A related issue is the wide range of approaches taken across different papers. Some models employ imperfect competition, while others don't. Some require search frictions, while others don't. These approaches beg the question: what is the *minimum* set of ingredients necessary to make demand-driven recessions viable?

This paper will contribute to the literature by proposing a feature which, alone, can render demand shocks contractionary. I will show that by introducing risk aversion on the side of producers, realistic business cycle behavior can be recovered in a model without nominal rigidities, search frictions, or adjustment costs. Two different types of demand-side shocks can trigger this effect: an uncertainty shock to future technology, and uncertainty over future consumer demand. I will argue that the later is more realistic of the two. These types of shocks are also considered in Bloom et al. (2012) and Basu and Bundick (2012). This paper corroborates their results in a simpler model, and proposes that risk averse firms are a general explanation for the action of such shocks.

5.2 Risk Averse Firms

To see why corporate risk aversion matters, imagine that an uncertainty shock compels consumers to engage in precautionary savings. In the absence of other effects, this will increase the supply of loanable funds and drive up investment. But note there is something deeply asymmetric about this story: why wouldn't firms, too, respond to this increase in uncertainty? In business surveys, uncertainty - particularly uncertainty about consumer demand, is often cited as the primary reason for firms laying off workers or scaling down operations (Lourenco and Lowe, 1994). After all, firms must frequently make long term inlays - whether it's installing capital or hiring workers, and the profitability of these decisions is highly contingent on the realizations of future macroeconomic variables.

This line of reasoning suggests that we treat firms (or their decision makers) as risk averse is a manner similar to households. To demonstrate the consequences of doing so, consider a simple two period model in which firms choose the optimal level of investment for the next period. In particular, imagine that firms profits in the first period is equal to output, investment and rents for capital.

$$\pi_1 = Ak^\alpha - rk - i, \;\; \alpha < 1$$

$$\pi_2 = A'(k+i)^\alpha - r(k+i)$$

In the second period, investment is installed as capital; for purposes of simplicity, we ignore depreciation and set the price of both output and a unit of investment to one. Suppose that in the next period, the level of technology in the economy is subject to an unknown shock, and distributed as follows:

$$A' = \begin{cases} A + \varepsilon, & Pr = \frac{1}{2} \\ A - \varepsilon, & Pr = \frac{1}{2} \end{cases}$$

In the absence of risk aversion, total expected profit for both periods is given by

$$E(\pi_T) = Ak^\alpha - rk - i + \frac{1}{2}\left[(A+\varepsilon)(k+i)^\alpha - r(k+i) + (A-\varepsilon)(k+i)^\alpha - r(k+i)\right]$$

$$= Ak^\alpha - rk - i + A(k+i)^\alpha - r(k+i)$$

Unsurprisingly this expression is invariant in epsilon, the magnitude of uncertainty regarding future productivity. The linearity of the productivity parameter α in the firm's profit equation ensures that an uncertainty shock has no effect. Now imagine that that firms maximize not total profit, but a concave function of in-period profit, just as consumers maximize a concave function of in-period consumption. In this simple example, the CRRA utility function will be used.

$$u(\pi_t) = \frac{\pi_t^{1-\sigma}}{1-\sigma}$$

Expected utility across the two periods is now given by

$$E(u_T) = A \cdot k^a - rk - i + \frac{1}{2}\left[(A+\varepsilon)\cdot(k+i)^a - r\cdot(k+i)\right]^{1-\sigma} + \frac{1}{2}\left[(A-\varepsilon)\cdot(k+i)^a - r\cdot(k+i)\right]^{1-\sigma}$$

Figure 14plots this total utility as a function of investment for a varying levels of epsilon and sample parameter values ($\alpha = \frac{2}{3}, \sigma = 0.6$).[11] Note that as the level of uncertainty increases in the economy, the optimal level of investment falls. It's not difficult to see why. When epsilon is high, the level of capital which maximizes second period profits is large, encouraging high investment in the first period. However, the payoff from this high profit state is subdued due to the concavity of the utility function. Thus,

[11] For particular values of α and σ, this simple model can be solved analytically; I do this in appendix A.

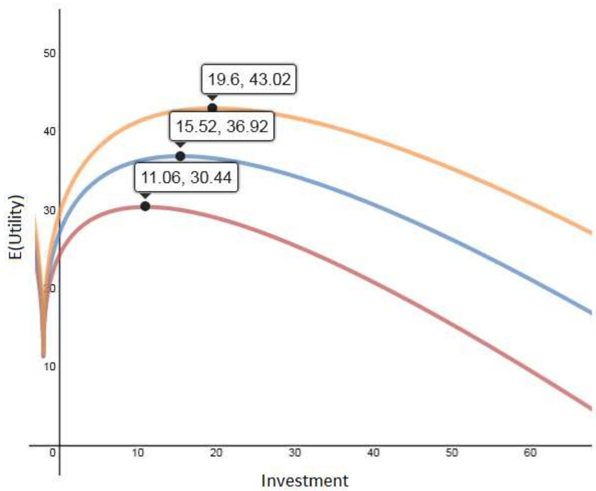


Figure 14: Expected Utility from Profits as a Function of Investment, Under Varying Levels of Uncertainty: top, $\varepsilon = 0$, middle, $\varepsilon = 85$, bottom, $\varepsilon = 100$.

while a high level of capital is heavily rewarded in the high technology state, it is even more heavily punished in the low technology state. The risk averse firm therefore reduces levels of investment in response to increased economic uncertainty. This reduction in investment demand is exactly what is needed to stop the increase in investment which plagues models attempting to trigger a recession using a demand shock. Even if households save, total investment can fall if firms' demand curve for investment shifts far enough to the left. In the full model below, the pattern exhibited by this two-period case will be borne out in a general equilibrium context.

5.3 Evidence that Firms are Risk Averse

Relatively few papers feature models with risk averse firms, particularly within a DSGE framework[12]. Acknowledging this, I wish to present some independent arguments that this assumption isn't unreasonable, and to address some possible concerns.

Executive Compensation The easiest way to imagine a risk averse firm is to simply assume that that the manager of the firm collects the profits as income. Since individuals are known to be risk averse in consumption levels, this would automatically imply that the firm behaves in a risk averse manner. This assumption holds for a privately owned sole proprietorship; some 75% of all US business are organized in this manner. However, it must be admitted that while sole proprietorships account for a great number of firms, they are responsible for only 5% of all sales[13].

But even in a large corporation, there is abundant evidence that manager's salaries, bonuses and other compensations are closely linked to the firm's profitability. Hall and Liebman (1998) use detailed firm level data and find that improving company performance from the industry median to the 70th percentile increases CEO salaries by some two million dollars, while diminishing firm performance from the median to the 30th percentile causes compensation to fall by roughly the same amount. In general, they estimate the elasticity of CEO's total compensation to firm profits to be on the order of 3.9, with this figure nearly tripling between 1980 and 1994. This effect is further exacerbated by the fact that in large corporations, senior managments' compensation increasingly takes the form of stock options. It's also been shown that stock performance is concave in profitability - investors punish unexpected negative profits more than they rewards unexpected positive profits (Lopez & Rees, 2002). Note that since this concavity arises in

[12]Notable exceptions include Sandmo (1971), Pindyck (1982), and Carceles Poveda (2003)

[13]Corporations, which are the opposite of a sole proprietorship in the sense of separating the firm's assets from those of its employees, account for 19% of all firms but 87% of total sales

the level of executive compensation itself, not the utility derived from it, it would result in risk averse behavior even if managers themselves were risk neutral in consumption levels.

Cash Holding An additional line of evidence comes from firms' cash holding behavior. Numerous studies suggest that firms hold cash reserves in order to hedge against borrowing constraints and adverse economic shocks (Almedia et al, 2004, Faulkender and Wang, 2006). The latter paper presents a theoretical model in which firms, particular those who are financially constrained, should increase cash retention when faced with negative economic shocks and find empirical evidence to this effect. Interestingly, a line of research in the behavioral literature suggests that this precautionary cash holding is not only subject to rational considerations such as borrowing ability, but also the personal experience of decision makers. For example, managers who grew up during the great depression (Malmendier et al, 2010), or who have been previously employed at firms facing financial difficulties (Dittmar and Duchin, 2012) hold larger reserves and are more averse to debt.

Business Insurance A final piece of evidence for corporate risk aversion is the existence of business insurance. Firms of varying sizes routinely insure themselves against a variety of possible losses. These include property insurance, business interruption insurance, disaster insurance, and liability insurance both for worker injury and damages resulting from defective products. In net, some 57% of all insurance premiums are paid by businesses (Hoyt and Khang, 1999). What's more Mayers and Smith (1990) find that closely held corporations are more likely to purchase insurance than firms with less concentrated ownership, and cite risk aversion is the primary reason for these findings. Since no risk neutral agent would ever find it rational to purchase insurance, the popularity of such products among firms is strong evidence that corporations can behave in a risk averse manner.

The Fisher Separation Theorem A set of results in the complete markets literature may cast some doubt on the evidence above. The Fisher Separation Theorem states that in the presence of complete capital and insurance markets, firms will make investment decisions which maximize their net present value, regardless of their shareholder's attitudes towards risk. This theorem can be viewed a special case of Modigliani-Miller theorem regarding corporate financing, and more generally, a consequence of the Arrow-Debreu model of general equilibrium.

To understand why complete markets have this effect, imagine a firm owned by two partners who evenly split the company's earnings amongst themselves and who hold different attitudes toward risk. Now suppose that these partners must choose between two investment projects, a high risk project with a greater expected return, and a low risk project with a smaller expected return. In the absence of complete markets, the two partners might disagree on which project to engage, with the risk averse partner favoring the low risk project despite the fact that this project does not maximize expected present value. However, if insurance markets are complete, it would be rational for the risk loving partner to offer to pay his more hesitant counterpart in the event that the risky project falls through. If such contracts are drawn optimally, shareholders will always find it rational to make the "pie as big as possible", maximizing the present value of the firm's income stream.

This heuristic example, while simplistic, also captures some potential pitfalls with this line of thought. In most publicly held corporations, conflicts of interest between management and shareholders are common (Fizel & Kenneth, 2006; Jensen & Murphy, 1990). The problem is that in contrast to the above example, not all shareholders are created equal; in particular, some are directly employed by the firm (as in the case of senior management), and some are not (in the case of a board member who is otherwise unrelated to the firms' operations). Shareholders directly employed by the firm are subject to that firms' internal compensation system, and well as organizational and behavioral forces such as intra-firm politics. What's more, there is a large information asymmetry between a CEO with detailed knowledge of the firm's internal working and projects, and a shareholder who is not employed by the corporation. All of these factors suggest that markets are not complete in the strong sense required by the Fisher theorem, and that the risk attitudes of individual decision makers in firms are relevant in determining that firm's investment choices.

6 Model

Firms To illustrate the effect of corporate risk aversion, the rest of the model is deliberately kept as simple as possible. A competitive firm produces a single consumption good with Cobb-Douglas technology, taking capital and labor as inputs. Since many papers which explore the effects of uncertainty also include capital adjustment costs, these are introduced in the standard way and will be turned off when analyzing the effects of risk aversion alone. The key feature of the model is that firms maximize the present discounted value of a concave function of profits. This is exactly analogous to consumer's intertemporal utility function; in fact, as discussed previously, this can be viewed as the problem of an entrepreneur whose consumption is dictated by the income of her firm.

$$\max_{k_t,l_t,i_t} : E_0 \sum_{t=0}^{\infty} \beta_f^t u\left[\pi_t\left(k_t, l_t\right)\right]$$

$$k_{t+1} = (1-\delta)\, k_t + i_t$$

$$\pi(k) = z_t f(k_t, l_t) - r_t k_t - w_t l_t - \Phi\left(\frac{i_t}{k_t}\right) k_t$$

$$u(\pi_t) = \frac{\pi_t^{1-\sigma_f}}{1-\sigma_f}$$

$$f(k_t, l_t) = k_t^{\alpha} l_t^{1-\alpha}$$

$$\Phi\left(\frac{i_t}{k_t}\right) = \gamma_1 \left(\frac{i_t}{k_t}\right)^{\gamma_2}$$

Households Households are also standard, supplying labor elastically and maximizing over a King Plosser & Rebelo utility function. To model first and second moment changes to consumer demand, the households' discount beta factor follows an AR-1 process. A utility function which is non-separable in consumption and labor is chosen because in the separable case, indeterminacy is found across a wide range of parameter values. This is related to the result reported by Chin, Guo, and Lai (2012), who find indeterminacy in a model with adjustment costs when the steady state wage-hours locus is steeper than households' labor supply curves.

$$\max_{c_t,l_t,k_t} : E_0 \sum_{t=0}^{\infty} \beta_{h_t}^t a_t u_t\left(c_t, l_t\right)$$

$$u_t = \frac{1}{\sigma_h}\left[c_t(1-l_t)^{\psi}\right]^{\sigma_h}$$

$$c_t + i_t = w_t l_t + r_t k_t$$

$$k_{t+1} = (1-\delta)\, k_t + i_t$$

In many models that feature capital adjustment costs, households own the capital stock and incur those costs, while myopic firms profit maximize in each period by setting the rental rate of capital equal to it's marginal product. In such a model, firms are only interested in the present period and can't exhibit the dynamic effects (such as precautionary behavior) that this paper explores.

In contrast, households and firms in this model each make an investment decision separately. For households, capital constitutes the only savings asset. By investing, households sacrifice current consumption in exchange for receiving an income stream rk, paid for by firms. On the other hand, firms also make the choice to install or remove capital. For firms, holding additional capital means that more output can be produced in the next quarter, at the drawback of paying households rk and incurring adjustment costs $\Phi\left(\frac{i_t}{k_t}\right)$. Note that firms do not "buy" capital from households, nor can they "sell" their capital stock to increase present period profits. The most intuitive way to interpret this model is to imagine that in each period, household savings are loaned to the firm through a frictionless financial intermediary. Firms use this money to install capital, and are charged interest accordingly. Liquidating capital simply means firms returning the money to households, who then use it to increase consumption.

Both household and firm investment decisions are contingent on the value of the r_t, which serves to clear the market for investment in this model. In the context of an negative demand shock (say, due to an unexpected rise in economic uncertainty), households wish to consume less and save more. On the other hand, firms view this demand shock as a reason to liquidate capital, since consumer demand implies lower output, thus lowering the profit maximizing level of capital for the subsequent period.

Shocks The model features first and second moment shocks to both the technology parameter z_t and β_t. First moment shocks follow the typical AR-1 process, with the added feature that the variance of each shock is itself an endogenous variable and governed by it's own AR-1 sequence. This follows the approach taken in Bloom et al. (2012) and Basu and Bundick (2012).

$$\beta_{t+1} = \rho_\beta a_t + \sigma_\beta e_{\beta_t}$$

$$\sigma_{\beta_{t+1}} = \sigma_{\beta_{ss}}(1-\rho_{\sigma_\beta}) + \rho_{\sigma_\beta}\sigma_{\sigma_\beta} + u_{\beta_t}$$

$$z_{t+1} = z_{ss}(1-\rho_z) + \rho_z z_t + \sigma_{z_t} e_{z_t}$$

$$\sigma_{z_{t+1}} = \sigma_{z_{ss}}(1-\rho_{\sigma_z}) + \rho_{\sigma_z}\sigma_{z_t} + u_{z_t}$$

Implementation Computation implementation of the above model was preformed in dynare using a third order Taylor approximation about the deterministic steady state. As discussed in Basu and Bundick (2012), a third order expansion is the minimum needed to capture the effects of uncertainty. In addition, the Blanchard & Khan conditions, which give sufficient criterion for stability in the linear case, no longer guarantee stability in the third order model. Following standard practice, the pruning algorithm created by Martin et al. (2013) is used to ensure nonexplosive behavior.

6.1 Governing Equations

Solving the maximization problem described above yields the following system of nonlinear difference equations.[14]

- Investment Demand

$$\pi_t = z_t k_t^\alpha l_t^{1-\alpha} - r_t k_t - w_t l_t - \gamma_1 \left(\frac{i_t}{k_t}\right)^{\gamma_2} k_t$$

$$\frac{\beta_f\left[\alpha z_{t+1} k_{t+1}^{\alpha-1} l_{t+1}^{1-\alpha} - r_{t+1} - \gamma_1(1-\gamma_2) i_{t+1}^{\gamma_2} k_{t+1}^{-\gamma_2} + (1-\delta)\gamma_1\gamma_2 i_{t+1}^{\gamma_2-1} k_{t+1}^{1-\gamma_2}\right]}{(\pi_{t+1})^{1-\sigma_f}} = \frac{\gamma_1\gamma_2 i_t^{\gamma_2-1} k_t^{1-\gamma_2}}{(\pi_t)^{1-\sigma_f}}$$

- Investment Supply

[14] For simplicity, the expected value operator has been omitted from the beginning of each expression.

$$\left(\frac{a_t}{a_{t+1}}\right)\left(\frac{c_{t+1}}{c_t}\right)^{1-\sigma_h}\left(\frac{1-l_t}{1-l_{t+1}}\right)^{\psi\sigma_h} = \beta_h(1+r_{t+1}-\delta)$$

- Labor Demand

$$(1-a)z_t\left(\frac{k_t^{\alpha}}{l_t^{\alpha}}\right) = w_t$$

- Labor Supply

$$\psi c_t = w_t(1-l_t)$$

- Capital Evolution

$$k_{t+1} = (1-\delta)k_t + i_t$$

- Economy-Wide Budget Constraint

$$c_t + i_t + \gamma_1\left(\frac{i_t}{k_t}\right)^{\gamma_2} k_t + \pi_t = z_t k_t^{\alpha} l_t^{1-\alpha}$$

- Shock processes

$$a_{t+1} = \rho_a a_t + var_a e_{a_t}$$

$$var_{a_{t+1}} = \rho_{var_a} var_{a_t} + u_{z_t}$$

$$z_{t+1} = z_{ss}(1-\rho_z) + \rho_z z_t + \sigma_{z_t} e_{z_t}$$

$$\sigma_{z_{t+1}} = \sigma_{z_{ss}}(1-\rho_{\sigma_z}) + \rho_{\sigma_z}\sigma_{z_t} + u_{z_t}$$

6.2 Baseline Calibration

The following table summarizes the choice of parameters in the baseline calibration of the model. Where possible, values which have reached consensus in the literature are used. For the parameters of the firms' utility function, figures similar to households are chosen, keeping with the idea that firm-level risk aversion arises from risk attitudes of individuals operating those firms. For parameters whose value is unsettled, I analyze the model over the full range of values found in the literature - see the results section for more details. Finally, for the AR-1 parameters of the second moment shocks, I use the values in Basu & Bundick (2012). The results section will show that the performance of the model is not particulary sensitive to these parameters.

Parameter	Description	Value	Range in Literature
	Firms		
α	Capital Share	0.33	Consensus
δ	Depreciation Rate (Quarterly)	0.025	Consensus
ϕ_1	Adj. Cost Level	0.1	$[-1.75, 20]$[a]
ϕ_2	Adj. Cost Convexity	2	Consensus
β_f	Discount Factor for Profits	0.95	Novel Parameter
σ_f	Firm Risk Aversion	2	Novel Parameter
	Households		
χ	Disutility of Labor	0.35	Consensus
σ_h	Household Risk Aversion	2	Consensus
	Tech. Shocks		
z_{ss}	Steady State Tech. Level	1	Consensus (by convention)
ρ_z	Persistence of 1st Moment Shocks	0.99	$[0.85, 1]$[b]
$\sigma_{z_{ss}}$	Steady State Volatility	0.01	[0.0032, 0.063][c]
ρ_{σ_z}	Persistence of 2nd Moment Socks	0.83	Few Estimates, use B&B
σ_{u_z}	Volatility of 2nd Moment Shocks	0.0017	Few Estimates, use B&B
	Preference Shocks		
β_{ss}	Steady State Discount Factor	0.99	Consensus
ρ_β	Persistence of First Moment Shocks	0.90	[0.82,0.98][d]
$\sigma_{\beta_{ss}}$	Steady State Volatility	0.02	[0.01,0.569][e]
ρ_{σ_β}	Persistence of 2nd Moment Socks	0.83	Few Estimates, use B&B
σ_{u_β}	Volatility of 2nd Moment Shocks	0.0017	Few Estimates, use B&B

Table 7: Baseline Parameterization and Comparison to Values Used in Literature

[a] Cooper and Haltiwanger(2006), Hayashi (1982)
[b] Gali & Rabanal (2005), Dedola & Neri (2006)
[c] Sims (2011), Bloom (2011)
[d] Primiceri et. al (2006), Yi (2006)
[e] Basu and Brent (2012), Primiceri et. al (2006)

7 Results

Summary

In the baseline parameterization, both technological and discount factor uncertainty shocks are found to be contractionary, while a positive first moment discount factor shock is expansionary. This implies that while a demand shock due to a true increase in patience cannot trigger a recession in this model, a demand shock arising from increased uncertainty can.

For uncertainty with respect to consumer demand (that is, a second moment shock to the discount factor), increasing the degree of firm risk aversion worsens the recession, while increasing the degree of household risk aversion moderates it. This is consistent with a picture in which precautionary behavior on both the firm and household side drive the economic response. For second moment technology shocks, these elasticities are more complex and may be non-monotonic.

Changing the adjustment cost parameters, and in particular, the convexity parameter, impacts not only the behavior of model variables, but their elasticities in both firm and corporate risk aversion. That is, the effects of increasing household's or firm's sigma can depend on adjustment costs. While the model exhibits indeterminacy in the total absence of such costs, both second moment shocks are still contractionary even if adjustment costs are set to vanishingly low values; this suggests that firm-side risk aversion is a sufficient condition for contractionary demand shocks in response to economic uncertainty.

Finally, in contrast to Yi (2006), the qualitative features of the above results are not found to be particularly sensitive to the persistence of the shock processes.

7.1 Baseline Economy

Figures 17 and 18 show impulse responses for all model variables under the influence of the three types of demand shocks discussed in the introduction. The impact of a negative first moment technology shock is also included for comparison. There are several things to learn from this baseline specification.

First Moment Shocks Figure one reveals that the standard negative technology shock leads to responses which are in line with business cycle stylized facts. In particular, output, hours worked, investment, and consumption are all seen to contract simultaneously. This robust and realistic co-movement between macroeconomic aggregates is why such shocks are so popular in the DSGE literature.

In contrast, a first moment demand shock leads to the counter-intuitive behavior discussed in the introduction - a failure of the so called "paradox of thrift". While an increase in consumer patience leads to a steep initial decline in consumption in favor of savings, this savings behavior drives up investment. Interest rates also rise, indicating that demand for investment is expanding as firms prepare to meet increased demand. In subsequent quarters, the expansion of the capital stock leads to a long lasting boom. Contemporaneous output also increases due to the labor market effect of the preference shock. Employment rises while wages fall, signaling an unambiguous expansion in labor supply; more patient households are willing to work more hours in order to accumulate savings. Overall, this economy could represent a society where increased prudence on the part of households leads to long term economic gains - a phenomenon which might be working in developing nations with high savings rates (Hamilton et al., 1999). However, it is clearly not appropriate for modeling a recession caused by a Keynesian reduction in aggregate demand.

Second Moment Shocks Turning to the second moment shocks, let's first examine the effects of an uncertainty shock on β_t, the consumer discount factor. Since this parameter governs the consumption-savings decision, such a shock would represent an increase in the uncertainty of future consumer demand. In response to this shock, both investment and interest rates fall simultaneously, consistent with a credit market dominated by a contraction in the demand for investment. As explained previously, the presence of firm side risk aversion, combined with the costs of adjusting the capital stock, means that firms reduce their demand for capital in response to increased economic uncertainty. This reduction in supply overwhelms the precautionary savings motive of households, leading to falls in investment which deplete the capital stock and trigger a long term fall in output. In general, this shock leads to the co-movement to be expected in a recession for all macroeconomic aggregates except for consumption.

But what about consumption? The fall in the demand for new investment means that interest rates are now so low as to deter savings. Consumers spend their incomes instead, causing an initial increase in consumption levels. Note that this increase is highly transitory, as falling capital levels eventually drag down income, leading to a realistic recession within a few quarters. Both papers by Bloom also find this initial consumption effect. While this bump is counter-factual, it is somewhat inevitable in this simple model. This issue will be further tackled in the discussion section below.

In contrast to these straightforward effects, the effects of a second moment technology shock are somewhat perplexing. The simultaneous fall of investment, combined with a slightly positive interest rate response suggests a reduction in investment supply. This is paradoxical, since households would be expected to save in response to increase uncertainty. The reduction in hours worked, combined with rising wages, corroborates this; it seems households are also not engaging in precautionary labor supply, as might be expected. Perhaps household risk aversion is not set sufficiently high in the baseline calibration, or perhaps some other effect is at work. This issue will be explored in the subsequent analysis.

Comparing Magnitudes Finally, we make an important observation about the sizes of these effects. Note that for similarly sized driving shock, the impulse responses to second moment shocks are always several orders of magnitude weaker than their first moment counterparts. This suggests that in order for uncertainty shocks to drive a recession, the magnitude of such shocks must be very large - possibly hundreds of times larger than a first moment technology shock with the same contractionary impact. Is a shock of such size plausible? In the discussion section, I will present empirical evidence that the answer to this question is yes. While real variables such as technology or consumer patience may not shift more than a few percent over the course of the business cycle, there is reason to believe that perceptions about the variance of these quantities are highly variable.

7.2 The relative effects of household and firm risk aversion

As explained above, the behavior of the economy in this model is primarily driven by the impact of the shock on investment. This, in turn, is driven by the interplay between households and firms, who control the supply and demand for investment respectively. Therefore, the responses on both sides of the credit market to an uncertainty shock will depend on the risk aversion parameters σ_f and σ_h.

Figure 19 shows how the response of the credit market changes for varying levels of firm and household risk aversion. We turn to the second moment beta shock, and make two important observations. First, levels of investment and interest rates are negative and strictly decreasing in σ_f, the parameter governing firm risk aversion. This indicates that as firms become increasingly risk averse, the demand for investment shift leftwards. Picture a restaurant franchise closing some branches, or a factory eliminating some its machinery; this is exactly the behavior we would expect as risk averse firm owners, uncertain of future demand, precautionarily reduce the size of their capital stock.

Meanwhile, the degree of household risk aversion, σ_h controls the extent of precautionary savings on the part of households. This savings represents an increase in the supply of investment and helps to counteract the cutting-back of firms. If savings is sufficiently robust, this supply shift will dominate the credit market and lead to an increase in investment combined with a precipitous fall in interest rates. We see this behavior played out here; as households become more risk adverse, the contraction in investment becomes less pronounced and interest rates fall further. In this parameter domain, this effect is never enough to actually cause investment to become positive.

What about a second moment shock to technology, rather than consumer preferences? Here, the results are again somewhat surprising. First, note that investment levels sometimes rise as we increase risk aversion (the first line in the bottom left of figure 19), or are non-monotonic - first rising, then falling with σ_f (the forth line). What's more, increasing household risk aversion now leads to lower levels of investment and interest rates, the opposite as would be expected from an increase in the supply of investment. In fact, the co-movement of investment and interest rates while σ_h changes looks rather like a demand-side effect, rather than a supply side effect.

The solution to this puzzle may lie with the action of adjustment costs, which affect households both directly (via. an income effect) and indirectly through the expected value of future factor prices. This relationship is explored in the next set of figures.

7.3 How Risk Aversion Interacts with Adjustment Costs

Figures 20 through 23 show the reaction of investment and interest rates plotted against firm risk aversion, for different values of the adjustment cost parameter γ_1. Note that the response of these variables depends strongly on the level of adjustment costs, particularly for beta shocks. In the literature, the value of this parameter varies by several orders of magnitude. Estimates based on micro-level evidence differ widely from those obtained by targeting macroeconomic aggregates, such as the investment to capital ratio. However, note that while the slope of these lines vary as adjustment costs change, the overall response of the economy remains contractionary under both shocks. Whether costs are essentially turned off (g1 =0.01), or whether they are as large as those used in Basu and Bundick (2012), investment never crosses the x-axis. The next figure reports the same data, but for varying levels of household risk aversion. For technology shocks, the consistent decline in investment as risk aversion increases again suggests households are not engaging in precautionary saving.

The next two figures repeat this exercise, but vary the convexity parameter on adjustment costs, γ_2. Recent has emphasized the role of non-convexities, and even fixed costs, in the adjustment of capital (Cooper & Haltiwanger, 2005, Hall, 2004) . This suggests that the quadratic exponent on the popular form of adjustment costs used in this model is only a convention. Even admitting that adjustment costs are convex, there is of course no a-priori reason to believe that the degree of convexity is always equal to two. The figures show that the response of the economy depends heavily on the value of parameter, though the shocks remain contractionary under the vast majority of parametrizations. What's more, the elasticity of investment with respect to the risk aversion parameters varies widely in γ_2, with non-monotonic behavior exhibited in most cases.

7.4 Robustness to Shock Persistence

Varying the persistence of the first moment shocks has more straightforward effects. Note that while the impact of persistence on the absolute magnitude of the response is significant, particularly in the range near one, the sign of the effect remains largely unchanged; both second moment shocks consistently deliver a contraction, with the size of the contraction peaking, unsurprisingly, when the shocks themselves are most persistent. These results differ from those reported in Yi (2006), who finds a very large impact of shock persistence on investment and output.

8 Discussion

8.1 Sufficient Criteria for Demand Driven Recessions?

A comparison of this model and those discussed in the literature review will show the model is considerably simpler. In particular, it lacks any form of nominal rigidities, multiple sectors, or search frictions. However, the model delivers a contractionary effect under both types of uncertainty shocks across a broad range of parameter values, including varying levels of firm risk aversion and adjustment costs. In light of the difficulties in generating realistic co-movement with a demand shock, this begs the question: what are sufficient conditions for such a shock to produce realistic business cycle behavior? Above, I argued that corporate risk aversion is the key, but here I wish to make a more subtle point. I suggest that the following two conditions are all that is necessary for contractionary demand-side shocks:

1. Firms which maximize a discounted stream of expected future profits, rather than myopically maximizing profits in each period

2. Some kind of concavity in returns to investment

Careful examination of the list of models in Table 1 reveals that all of the models possess these two features. Firms are forward looking, either due to making an investment choice, or because nominal rigidities force firms to consider future periods when adjusting prices. Concavity in returns to investment can take the form of risk aversion, as in my model, or any number of adjustment or search frictions which punish firms for over-investing.

To illustrate this, consider a modified version of the model explored in this paper, but one in which firms maximize in-period profits only. Since firms are now myopic, the investment decision now entirely falls on the shoulders of households, who are risk averse and pay adjustment costs. In simple models of capital adjustment (such as those exploring Tobin's Q), this setup is actually much more common.

$$\max_{c_t,l_t,k_t} : E_0 \sum_{t=0}^{\infty} \beta_h^t a_t u_t\left(c_t, l_t\right)$$

$$u_t = \frac{1}{\sigma_h}\left[c_t(1-l_t)^{\psi}\right]^{\sigma_h}$$

$$c_t + i_t + \Phi\left(\frac{i_t}{k_t}\right) = w_t l_t + r_t k_t$$

$$k_{t+1} = (1-\delta)\,k_t + i_t$$

Comparing these models side by side is revealing. The Euler equation defining household consumption is nearly identical to the previous expression of capital demand for firms. In the new model, firms are no longer forward looking, and instead, myopically set the marginal products of labor and capital to their respective factor prices.

$$\beta_h\left[\frac{\alpha z_{t+1}k_{t+1}^{\alpha-1}l_{t+1}^{1-\alpha} - r_{t+1} - \gamma_1(1-\gamma_2)i_{t+1}^{\gamma_2}k_{t+1}^{-\gamma_2} + (1-\delta)\gamma_1\gamma_2 i_{t+1}^{\gamma_2-1}k_{t+1}^{1-\gamma_2}}{(c_{t+1})^{1-\sigma}(1-l_{t+1})^{-\sigma\psi}} = \frac{\gamma_1\gamma_2 i_t^{\gamma_2-1}k_t^{1-\gamma_2}}{(c_t)^{1-\sigma}(1-l_t)^{-\sigma\psi}}\right]$$

$$az_t(\frac{k}{l})^{a-1} = r_t$$

$$k_{t+1} \quad = \quad (1-\delta)k_t + i_t$$

$$\psi c_t = w_t(1-l_t)$$

$$k_{t+1} = (1-\delta)k_t + i_t$$

$$c_t + i_t + \gamma_1\left(\frac{i_t}{k_t}\right)^{\gamma_2} k_t = z_t k_t^{\alpha} l_t^{1-\alpha}$$

Figure 25 depicts the response of this economy to a second moment preference shock; note that the shock is now expansionary. Without a reduction in firm demand stemming from forward looking behavior, the investment market is dominated by households' precautionary behavior; in other words, it's dominated by an expansion in supply leading to greater investment, and ultimately, increased output.

8.2 The Right Uncertainty Shock

The papers which have considered second moment shocks to both technology and consumer preferences found largely similar results; the same can be said in this model, at least as far as investment and output are concerned. However, from a economic perspective, uncertainty in total factor productivity and uncertainty about consumer demand are certainly distinct concepts. This difference is important because as discussed in the results section, the magnitude of second order shocks are weak in comparison to their first order counterparts. As a result, second moment shocks must be greater than their first moment counterparts by several orders of magnitude in order to drive observable changes in the economy. In this section, I'll argue that agent's uncertainty over to consumer demand could approach these levels much more plausibly than agent's uncertainty over total factor productivity.

Measuring Economic Uncertainty Various measures of the level of economic uncertainty are reported in the literature. Bloom (2011) estimates uncertainty in total factor productivity using establishment level firm data and finds that the inter-quartile range between establishments in a given business is countercylcical. However, these vary by no more than 15% over his thirty year sample. In the model above, as parametrized, such shocks would be vastly insufficient to drive recessions of a realistic size.

Measures of the uncertainty of consumer demand are considerably uncommon. Leduc & Liu attempt to measure this uncertainty with three sources: the percentage of consumers reporting an "uncertain future" in the Michigan Survey of Consumers, a similar measure for a survey of firm owners in the UK, and the VIX index. The latter is a measure of volatility constructed from stock market data which is commonly used in the uncertainty literature. Again, though, none of these variables are observed to change by more than 15 percent over the course of the business cycle. Much of the problem results from the nature of the measures themselves; they are indicies constructed to range from 0 to 100. Such measures are not well suited for this quantitative exercise, where the absolute level of uncertainty really matters.

While it's difficult to characterize agent's subjective level of uncertainty, it is possible to evaluate the information set used by agents to make future decisions. He (2014) studies the differential delivery of pessimistic news across the United States during the previous two recessions. By combining information on newspaper subscribership with automatic content analysis of newspaper articles, it's possible to estimate the quantity of pessimistic news delivered to each US county by each news source. Figure 15 plots the variance of this information as a function of time. The methods used to compute this graph are discussed in the paper; for our purposes, it's sufficient to understand that this variable characterizes the dispersion of news about the economy, as experience by readers in a particular US county. This number will be equal to zero if all newspapers sources in a given county report the same number of economically pessimistic articles in a given quarter, or if all readers in a county subscribe to the same source. Averaging across the United States, we find that this variable increases by roughly two orders of magnitude during economic contractions.

Figure 15: County level measures of the dispersion of pessimistic news. National average is plotted for past two recession.

On larger geographic scales, the level of news pessimism with regards to the economy varies strongly geographically. Pic 16 depicts this variation, expressed as percentage deviation from the national mean. Imagine that the manager of a large restaurant franchise receives information from his various subsidiaries across the country. If each subsidiary reports the average level of pessimistic news circulating in that county, the number of different opinions heard by this manager would be substantial, and would increase dramatically as the economy begins to contract. Therefore, it is quite plausible that uncertainty with regards to consumer demand could vary by several orders of magnitude, as the above model requires.

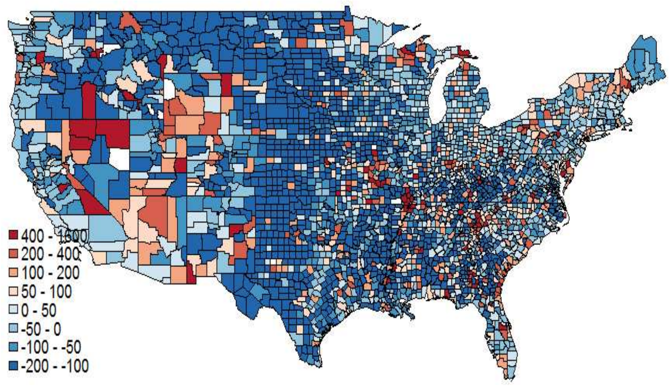


Figure 16: Geographic variation in pessimistic news delivery, Q2 2008.

8.3 Fixing the Consumption Overshoot

There remains one problem with the model: the consumption overshoot experienced initially as interest rates fall and households reduce savings. Bloom also finds this effect in both of his papers; he deals with it by simultaneously introducing a first order shock to technology. If the magnitude of this shock is correctly calibrated, it will cancel out the increase in consumption and deliver realistic co-movement across all macroeconomic variables. However, given that the intention of this literature is to suggest an alternative to technology shocks, this solution seems sub-optimal.

A more realistic way to deal with the issue would be to introduce search and matching into the financial section. Consider the situation on the eve of a recession, it's very likely that consumers are reducing consumption and saving more money. But this does not necessarily have to mean that investment must rise. In reality, savings and investment don't automatically equate; there is the entire financial industry devoted to matching the two. If households wish to save but firms don't wish to borrow, excess capital can simply sit around in bank vaults. This is analogous to excess inventories in good search and matching, and to unemployment in the labor market - there's nothing mysterious about financial markets not clearing immediately. Such a model would allow the above effects to operate without the counter-factual overshoot in consumption, and would be an interesting avenue for future work.

9 Conclusion

The DSGE literature has long recognized the difficulty of generating realistic business cycle dynamics using shocks to aggregate demand. In contrast to intuition, a sudden reduction in consumer demand leads to economic expansion, since resources which would otherwise be consumed are instead used for investment. This paper proposes a novel mechanism to resolve this issue: risk averse behavior on the side of firms. It finds that even in a bare-bones DSGE framework, risk-averse firms can deliver realistic business cycle co-movement in response to demand shocks triggered by increased economic uncertainty. These results suggest that uncertainty, and in particular, firms' uncertainty with regards to future consumer demand, plays a significant role in business cycle contraction.

Part III

Tables

	(1) OLS	(2) Cnty, Qtr	(3) Cnty, Qtr	(4) Cnty, St*Qtr	(5) Cnty, Qtr	(6) Cnty, St*Qtr
Articles per Person	-0.0091***	-0.0013**				
	(0.000)	(0.049)				
(1st lag)	-0.0015	0.0002				
	(0.150)	(0.794)				
APP, No local/jobs			-0.0042***	-0.0021		
			(0.000)	(0.151)		
(1st lag)			0.0016	-0.0017		
			(0.201)	(0.286)		
No Local/Jobs, Natl					-0.0429***	-0.0146
					(0.001)	(0.304)
(1st lag)					0.0025	0.0141
					(0.856)	(0.348)
Observations	86655	86655	86655	86655	86655	86655
R^2	0.889	0.966	0.966	0.970	0.966	0.970
F	1.9e+04	814.6556	814.7534	628.7516	815.0341	628.6528

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. All specifications include the covariates listed in table 4. For full table with all covariates, see appendix.

Table 8: Effects of Pessimistic News on Logged Total Employment

	(1) OLS	(2) Cnty, Qtr	(3) Cnty, Qtr	(4) Cnty, St*Qtr	(5) Cnty, Qtr	(6) Cnty, St*Qtr
Articles Per Reader	-0.0019***	-0.0000				
	(0.000)	(0.931)				
(1st lag)	-0.0010***	-0.0003*				
	(0.000)	(0.099)				
APR, No Local/Jobs			-0.0008**	-0.0007*		
			(0.036)	(0.074)		
(1st lag)			-0.0001	-0.0004		
			(0.827)	(0.340)		
No Local/Jobs, Natl					-0.0054***	-0.0036**
					(0.008)	(0.041)
(1st lag)					-0.0007	0.0012
					(0.617)	(0.459)
Observations	86565	86565	86565	86565	86565	86565
R^2	0.889	0.966	0.966	0.970	0.966	0.970
F	1.9e+04	813.7174	813.8060	628.0047	814.2308	627.9109

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. All specifications include the covariates listed in table 4. For full table with all covariates, see appendix.

Table 9: Effects of Pessimistic News on Logged Hiring

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Cnty, Qtr	Cnty, Qtr	Cnty, St*Qtr	Cnty, Qtr	Cnty, St*Qtr
Articles per Person	0.0168***	-0.0051***				
	(0.000)	(0.004)				
(1st lag)	-0.0583***	-0.0038**				
	(0.000)	(0.025)				
APP, No local/jobs			-0.0099***	-0.0081**		
			(0.001)	(0.030)		
(1st lag)			-0.0068**	-0.0051		
			(0.023)	(0.174)		
No Local/Jobs, Natl					-0.0983***	-0.0298
					(0.004)	(0.403)
(1st lag)					-0.0458	0.0022
					(0.215)	(0.952)
Observations	85755	85755	85755	85755	85755	85755
R^2	0.642	0.828	0.828	0.849	0.828	0.849
F	4.2e+03	134.7811	134.7913	107.1097	134.8174	107.0764

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. All specifications include the covariates listed in table 4. For full table with all covariates, see appendix.

5. Hiring refers to new stable hires, defined as total number of workers who were new hires by the employer in the last quarter and are full-quarter employed in the current quarter.

Table 10: Effects of Pessimistic News on Logged Hiring

	(1) OLS	(2) Cnty, Qtr	(3) Cnty, Qtr	(4) Cnty, St*Qtr	(5) Cnty, Qtr	(6) Cnty, St*Qtr
Articles Per Reader	0.0053***	-0.0016***				
	(0.000)	(0.001)				
(1st lag)	-0.0151***	-0.0004				
	(0.000)	(0.438)				
APR, No Local/Jobs			-0.0028***	-0.0028***		
			(0.001)	(0.006)		
(1st lag)			-0.0010	-0.0003		
			(0.259)	(0.811)		
No Local/Jobs, Natl					-0.0161***	-0.0076**
					(0.000)	(0.028)
(1st lag)					-0.0019	0.0017
					(0.587)	(0.685)
Observations	85665	85665	85665	85665	85665	85665
R^2	0.642	0.828	0.828	0.849	0.828	0.849
F	4.1e+03	134.5771	134.5862	106.9317	134.6335	106.9090

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. All specifications include the covariates listed in table 4. For full table with all covariates, see appendix.

5. Hiring refers to new stable hires, defined as total number of workers who were new hires by the employer in the last quarter and are full-quarter employed in the current quarter.

Table 11: Effects of Pessimistic News on Logged Separations

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Cnty, Qtr	Cnty, Qtr	Cnty, St*Qtr	Cnty, Qtr	Cnty, St*Qtr
Articles per Person	-0.0201***	-0.0005				
	(0.000)	(0.828)				
(1st lag)	0.0056**	-0.0042*				
	(0.017)	(0.059)				
APP, No local/jobs			-0.0103***	0.0020		
			(0.003)	(0.655)		
(1st lag)			0.0014	-0.0091**		
			(0.708)	(0.025)		
No Local/Jobs, Natl					0.0995***	0.0062
					(0.001)	(0.871)
(1st lag)					-0.1693***	-0.0437
					(0.000)	(0.298)
Observations	86370	86370	86370	86370	86370	86370
R^2	0.604	0.759	0.759	0.799	0.759	0.799
F	3.6e+03	88.7270	88.7311	75.9488	88.7559	75.9443

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. All specifications include the covariates listed in table 4. For full table with all covariates, see appendix.

5. Separations refers to separations from stable employment, defined as the total number of workers who are employed for the entire previous quarter at some employer but are not employed at that employer in the current quarter.

Table 12: Effects of Pessimistic News on Logged Separations

	(1) OLS	(2) Cnty, Qtr	(3) Cnty, Qtr	(4) Cnty, St*Qtr	(5) Cnty, Qtr	(6) Cnty, St*Qtr
Articles Per Reader	-0.0043***	0.0008				
	(0.000)	(0.195)				
(1st lag)	0.0003	-0.0021***				
	(0.539)	(0.001)				
APR, No Local/Jobs			-0.0015	0.0010		
			(0.154)	(0.421)		
(1st lag)			-0.0011	-0.0028**		
			(0.298)	(0.011)		
No Local/Jobs, Natl					0.0044	-0.0002
					(0.281)	(0.943)
(1st lag)					-0.0120***	-0.0027
					(0.009)	(0.439)
Observations	86280	86280	86280	86280	86280	86280
R^2	0.604	0.759	0.759	0.799	0.759	0.799
F	3.6e+03	88.6772	88.6685	75.8730	88.6669	75.8634

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. All specifications include the covariates listed in table 4. For full table with all covariates, see appendix.

5. Separations refers to separations from stable employment, defined as the total number of workers who are employed for the entire previous quarter at some employer but are not employed at that employer in the current quarter.

Table 13: Yearly Effects on Log. Tot. Employment During the Past Recession

	(1) 2007	(2) 2008	(3) 2009	(4) 2010
APP, No Local/Jobs, Natl.	-0.0885***	-0.0900	-0.0143	0.4471
	(0.001)	(0.236)	(0.489)	(0.640)
Observations	11584	11584	11584	5791
R^2	0.988	0.989	0.988	0.994
F	232.7322	254.4766	221.5136	144.8126

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Standard errors clustered at state-by-county level.

3. Specification identical to columns (4) and (6) in tables above.

Table 14: Yearly Effects on Logged Hiring During the Past Recession

	(1)	(2)	(3)	(4)
	2007	2008	2009	2010
APP, No Local/Jobs, Natl.	-0.2381**	-0.3261	-0.0155	3.4339
	(0.019)	(0.215)	(0.791)	(0.466)
(1st lag)	-0.0051	-0.2989**	0.1202**	-1.9327
	(0.978)	(0.027)	(0.040)	(0.397)
Observations	11566	11569	11564	5774
R^2	0.906	0.898	0.883	0.925
F	26.2675	24.0082	20.7785	11.4176

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Standard errors clustered at state-by-county level.

3. Specification identical to columns (4) and (6) in tables above.

Table 15: Yearly Effects on Logged Separations During the Past Recession

	(1)	(2)	(3)	(4)
	2007	2008	2009	2010
APP, No Local/Jobs, Natl.	0.0556	-0.0744	-0.1600**	-2.2953
	(0.666)	(0.836)	(0.020)	(0.677)
(1st lag)	0.1015	-0.3283	-0.0838	0.6723
	(0.529)	(0.109)	(0.373)	(0.819)
Observations	11575	11574	11573	5784
R^2	0.845	0.858	0.827	0.902
F	15.0008	16.5641	13.1132	8.5649

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Standard errors clustered at state-by-county level.

3. Specification identical to columns (4) and (6) in tables above.

Table 16: Impact of News by NAICS Sector

(1) Sector	(2) Coeff.	(3) 1/Coeff.	(4) p	(5) News-Worth
Accommodation and food services	-68.77	-0.01	0.220	1.33
Administrative and waste management services	-62.2***	1.00	0.010	0.03
Construction	-40.61*	-0.02	0.070	0.27
Retail trade	-33.84***	-0.03	0.000	0.44
Transportation and warehousing	-30.68***	-0.03	0.000	1.41
Real estate and rental and leasing	-24.55***	-0.04	0.010	4.77
Mining	-21.49**	-0.05	0.050	4.48
Finance and insurance	-13.36*	-0.07	0.080	8.64
Educational services	-8.4	-0.12	0.660	20.64
Information	-5.6	-0.18	0.510	1.60
Wholesale trade	-3.92	-0.25	0.590	0.04
Agriculture, forestry, fishing, and hunting	2.04	0.49	0.870	1.95
Utilities	4.93	0.20	0.220	127.35
Manufacturing	24.29	0.04	0.340	0.36
Management of companies and enterprises	25.77	0.04	0.170	0.00
Professional, scientific, and technical services	25.96	0.04	0.400	1.13
Health care and social assistance	30.44	0.03	0.110	6.27
Arts, entertainment, and recreation	31.26	0.03	0.180	4.78

1. Specification identical to columns (4) and (6) in Table **??**. Dependent variable is log of total employment
2. All coefficients scaled by 10,000 for readability.

Table 16: This table displays the effects of news disaggregated by industry, as well as an independent measure of news-worthiness.

Table 17: Articles Per Person, Single Source Counties

	(1) Tot. Emp.	(2) Hires	(3) Seps.	(4) Tot. Emp.	(5) Hires	(6) Seps.
APP, No Local/Jobs	-0.0020	-0.0056	0.0016			
	(0.253)	(0.235)	(0.830)			
(1st lag)	-0.0047**	-0.0158***	-0.0114*			
	(0.015)	(0.001)	(0.078)			
APP, No Local/Jobs, Natl.				-0.0243	-0.1015*	0.1435*
				(0.237)	(0.064)	(0.051)
(1st lag)				-0.0508**	-0.0851	-0.2560***
				(0.030)	(0.177)	(0.001)
Observations	30749	30415	30650	30749	30415	30650
R^2	0.967	0.832	0.816	0.967	0.832	0.816
F	704.7075	118.0309	51.3981	704.8111	117.9940	51.4204

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01
2. Specification identical to columns (4) and (6) in Table 6.
3. Single source counties are defined as counties in which at least 85 percent of all subscriptions are to the same newspaper.

Table 18: Articles Per Reader, Single Source Counties

	(1) Tot. Emp.	(2) Hires	(3) Seps.	(4) Tot. Emp.	(5) Hires	(6) Seps.
APR, No Local/Jobs	-0.0003	-0.0024**	0.0009			
	(0.569)	(0.041)	(0.620)			
(1st lag)	-0.0013***	-0.0023*	-0.0034*			
	(0.007)	(0.059)	(0.066)			
APR, No Local/Jobs, Natl.				0.0009	-0.0127	0.0090
				(0.655)	(0.109)	(0.124)
(1st lag)				-0.0037	-0.0014	-0.0107
				(0.313)	(0.822)	(0.149)
Observations	30659	30325	30560	30659	30325	30560
R^2	0.967	0.832	0.816	0.967	0.832	0.816
F	702.6174	117.5406	51.2664	702.1828	117.4716	51.2578

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01
2. Specification identical to columns (4) and (6) in Table 6.
3. Single source counties are defined as counties in which at least 85 percent of all subscriptions are to the same newspaper.

Table 19: Articles Per Person, Excluding Urban Areas

	(1) Tot. Emp.	(2) Hires	(3) Seps.	(4) Tot. Emp.	(5) Hires	(6) Seps.
APP, No Local/Jobs	-0.0027	-0.0112**	0.0008			
	(0.188)	(0.030)	(0.901)			
(1st lag)	-0.0015	-0.0077	-0.0102*			
	(0.480)	(0.133)	(0.075)			
APP, No Local/Jobs, Natl.				-0.0221	-0.0321	-0.0200
				(0.176)	(0.454)	(0.639)
(1st lag)				0.0257	-0.0038	-0.0183
				(0.139)	(0.932)	(0.706)
Observations	81176	80276	80891	81176	80276	80891
R^2	0.967	0.833	0.782	0.967	0.833	0.782
F	547.1458	92.5749	66.8497	547.0950	92.5354	66.8446

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01
2. Specification identical to columns (4) and (6) in Table 6.
3. Urban areas are defined as counties with popluation density greater than 500 persons per sq. mile.

Table 20: Articles Per Reader, Excluding Urban Areas

	(1) Tot. Emp.	(2) Hires	(3) Seps.	(4) Tot. Emp.	(5) Hires	(6) Seps.
APR, No Local/Jobs	-0.0008*	-0.0031***	0.0009			
	(0.098)	(0.007)	(0.538)			
(1st lag)	-0.0004	-0.0003	-0.0027**			
	(0.475)	(0.840)	(0.029)			
APR, No Local/Jobs, Natl.				-0.0038**	-0.0076**	-0.0011
				(0.034)	(0.034)	(0.761)
(1st lag)				0.0014	0.0011	-0.0018
				(0.404)	(0.795)	(0.617)
Observations	81086	80186	80801	81086	80186	80801
R^2	0.967	0.833	0.782	0.967	0.833	0.782
F	546.4049	92.3928	66.7716	546.3550	92.3726	66.7639

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01
2. Specification identical to columns (4) and (6) in Table 6.
3. Urban areas are defined as counties with popluation density greater than 500 persons per sq. mile.

Part IV

Figures

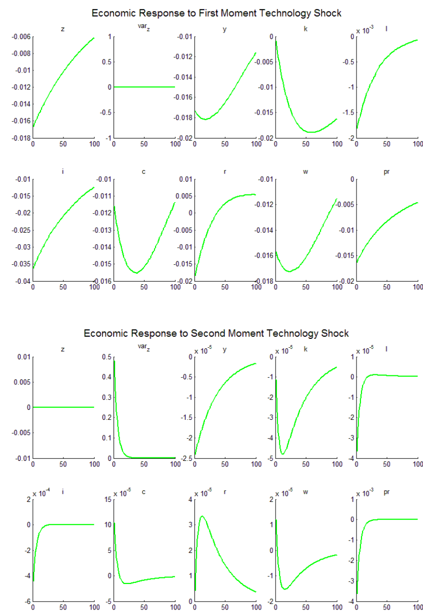


Figure 17: Impulse Response Functions for Technology Shocks in the Baseline Model.
"Pr" denotes in-period profits. All deviations expressed as percentage deviation from the ergodic mean.

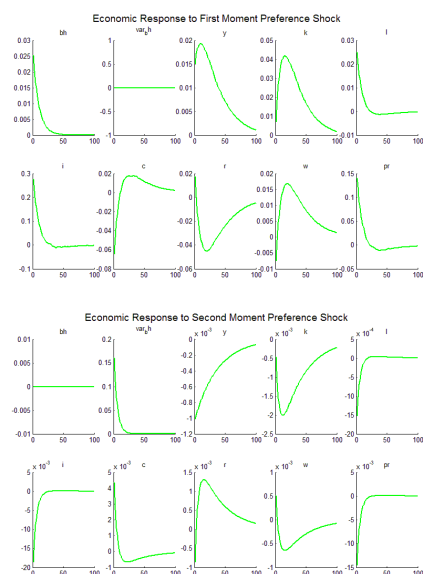


Figure 18: Impulse Response Functions for Consumer Preference Shocks in the Baseline Model - All deviations expressed as percentage deviation from the ergodic mean. Note that the initial response of consumption is anticyclical due to savings behavior.

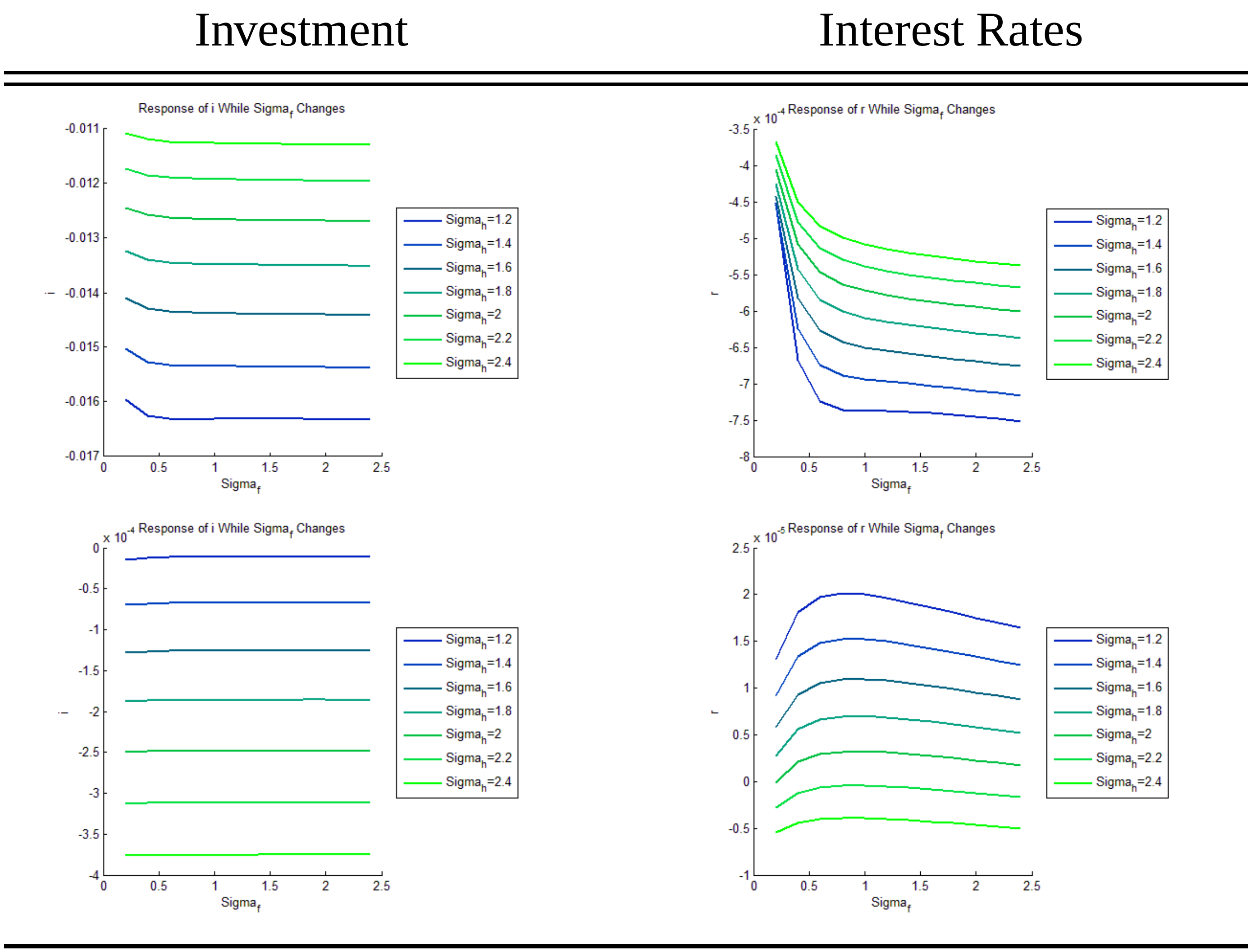


Figure 19: Responses of Investment and Interest Rates While Varying Household Risk Aversion ($Sigma_h$), for a second moment consumer preference shock (top), a second moment technology shock (bottom).

Investment	Interest Rates

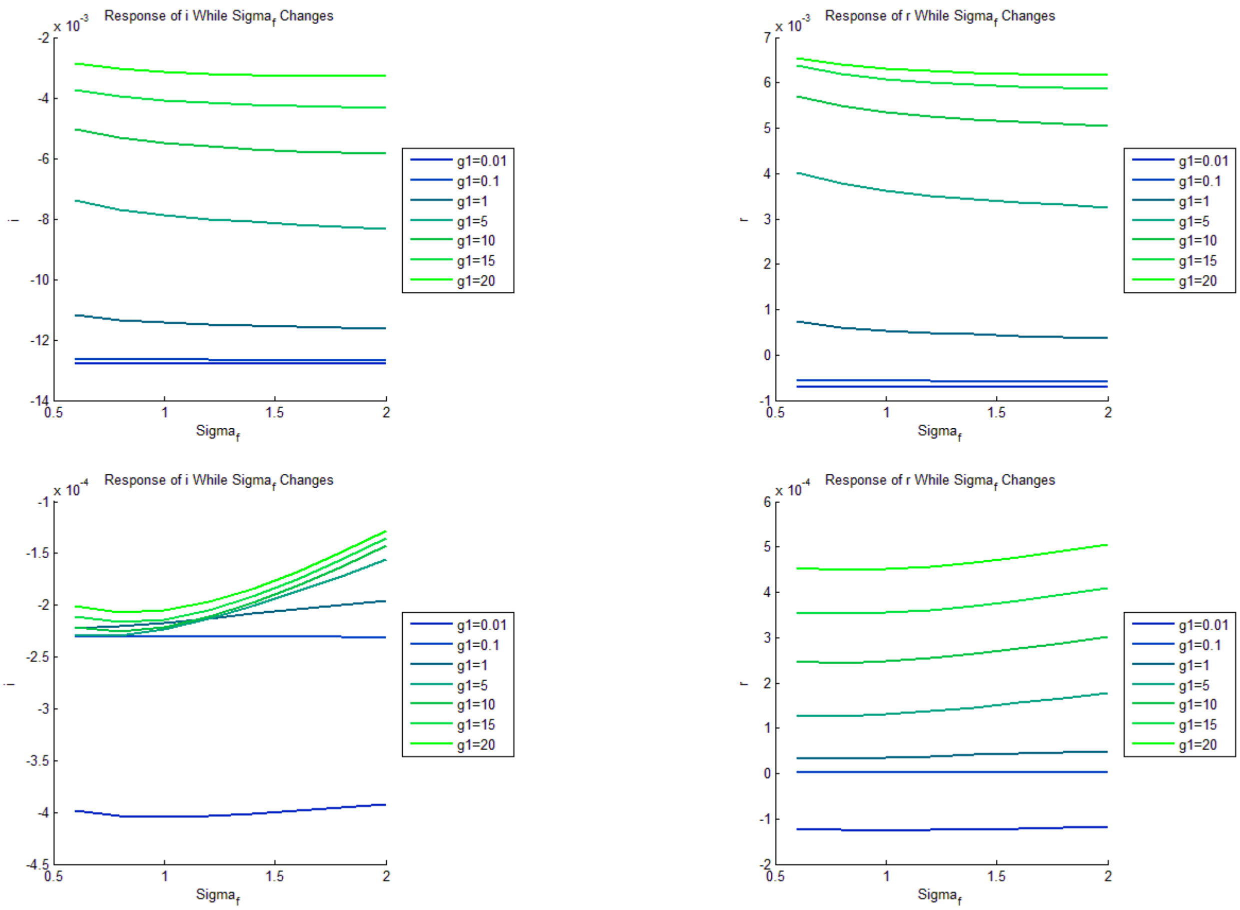


Figure 20: Differential responses of investment and interest rates while varying firm risk aversion ($Sigma_f$), for a second moment consumer preference shock (top), a second moment technology shock (bottom). Note the non-monotonicity in the repose, particularly for second moment technology shocks.

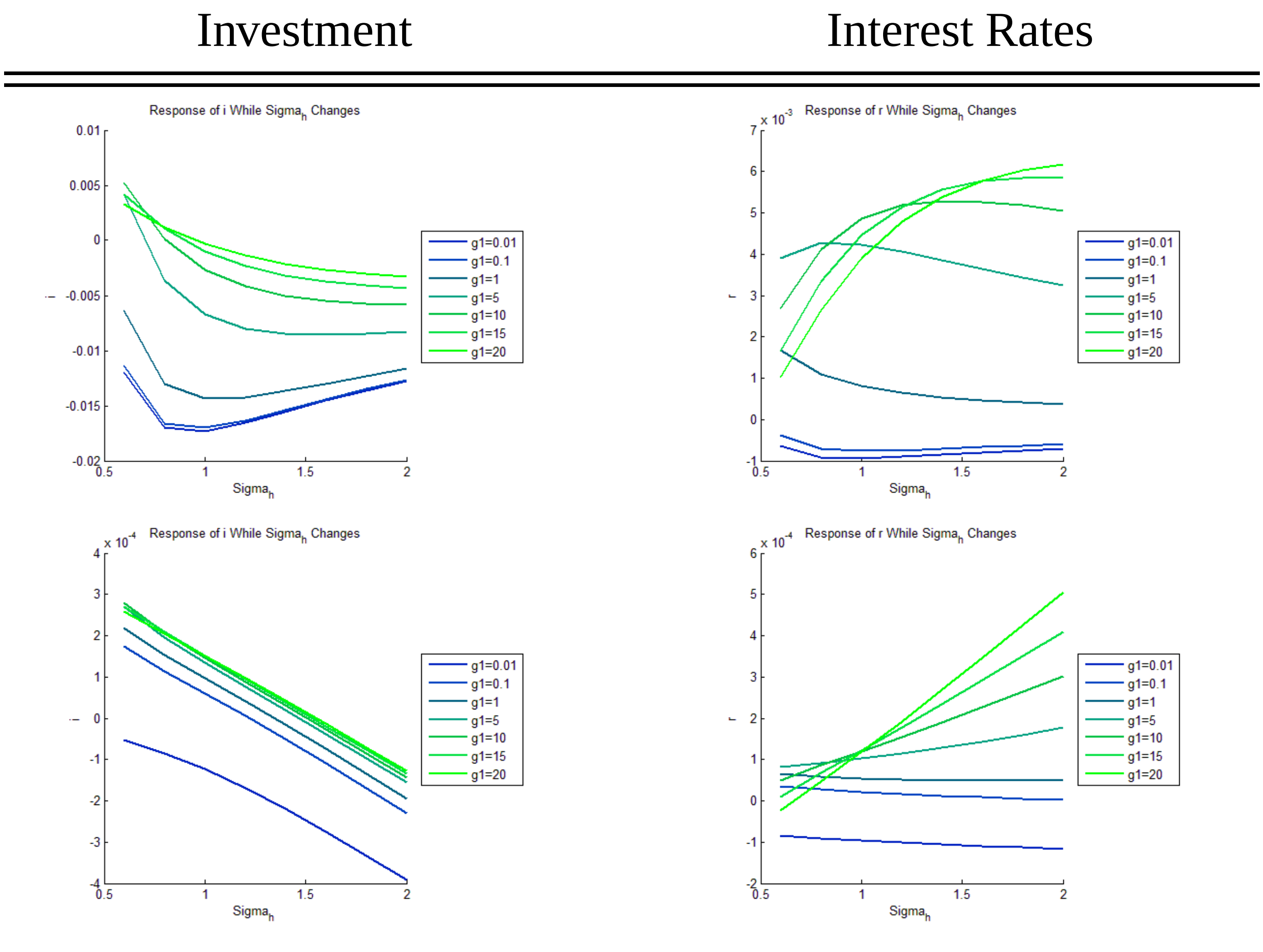


Figure 21: Differential responses of investment and interest rates while varying household risk aversion ($Sigma_h$), for a second moment consumer preference shock (top), a second moment technology shock (bottom).

Investment | Interest Rates

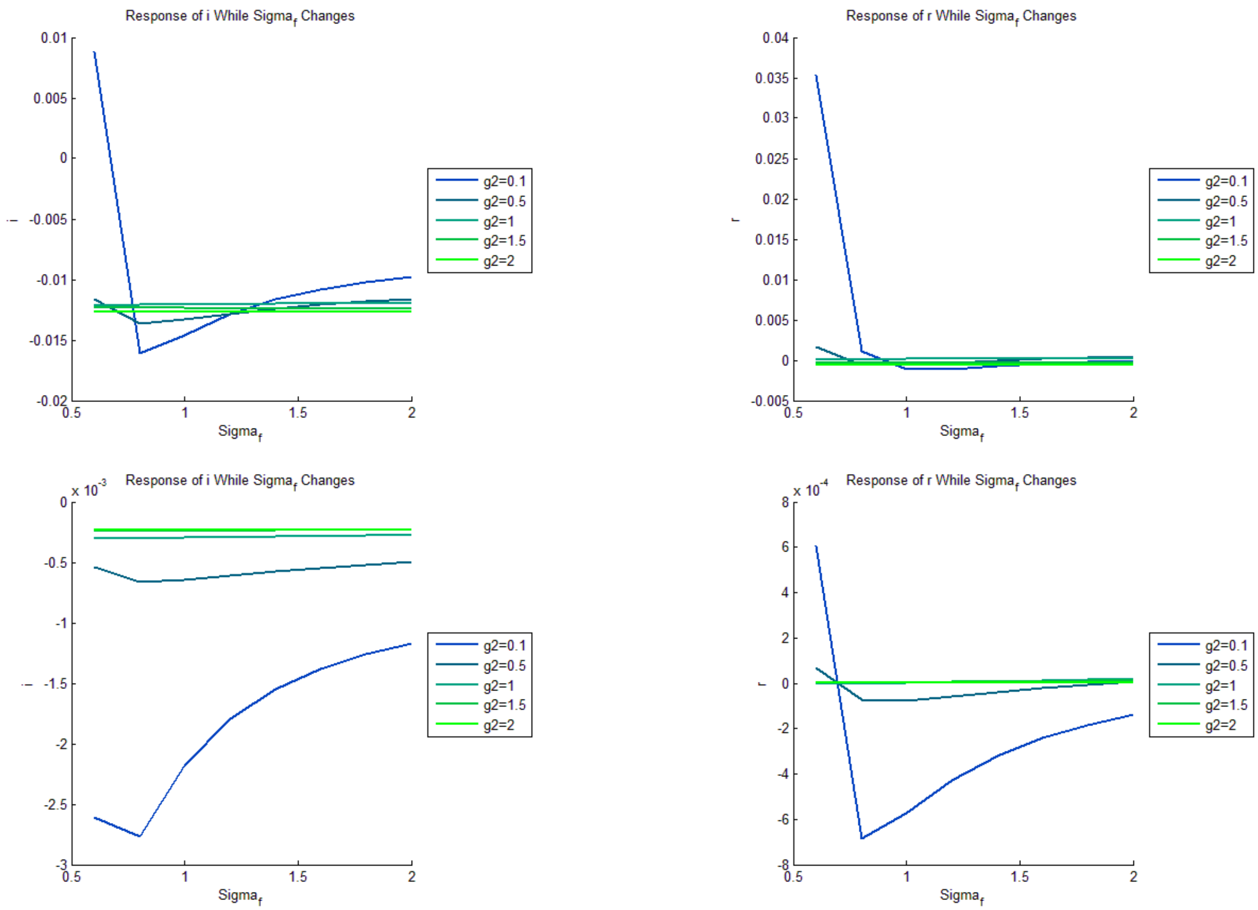


Figure 22: Differential responses of investment and interest rates while varying firm risk aversion ($Sigma_f$), for a second moment consumer preference shock (top), a second moment technology shock (bottom).

Investment Interest Rates

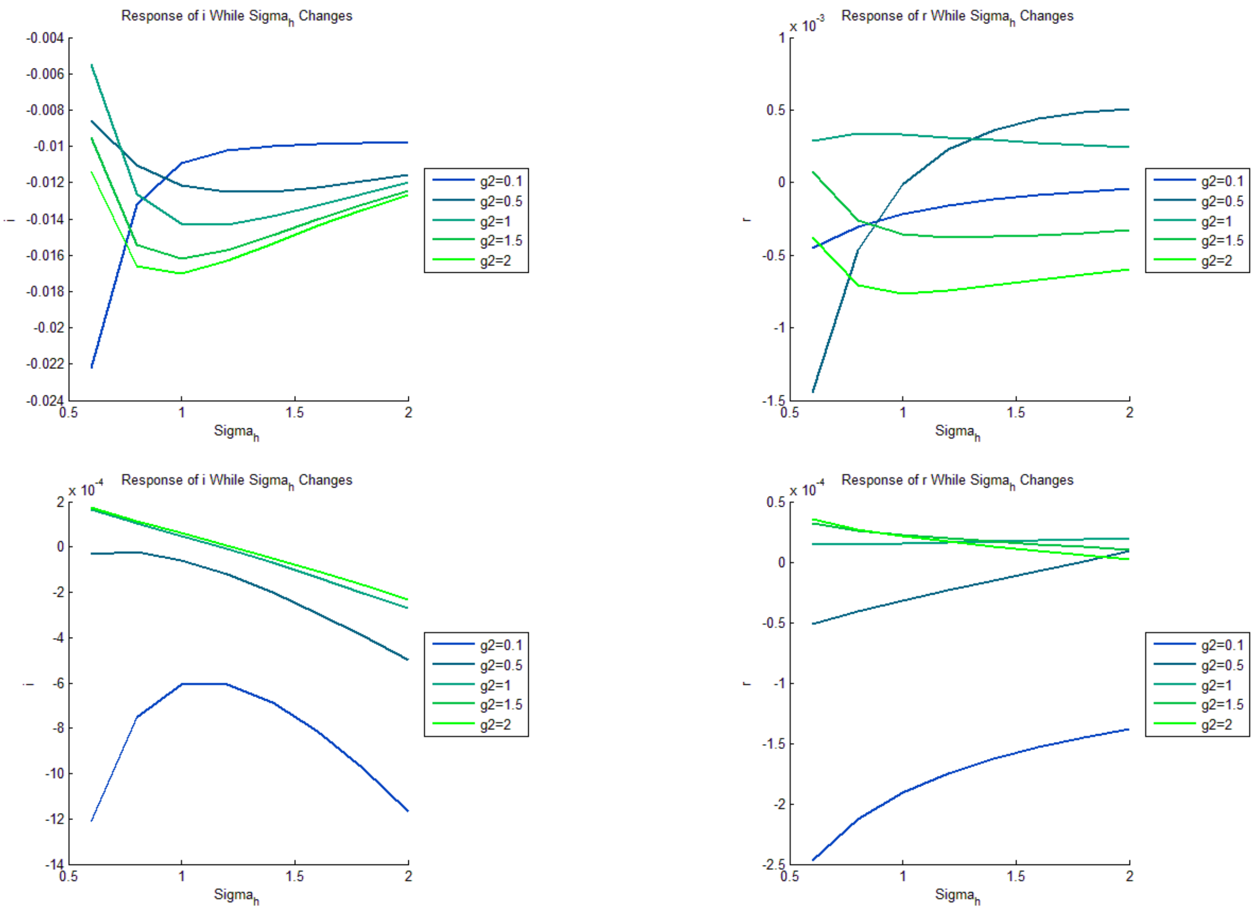


Figure 23: Differential responses of investment and interest rates while varying household risk aversion ($Sigma_h$), for a second moment consumer preference shock (top), a second moment technology shock (bottom). Note the non-monotonicity in the reponse for many values of gamma.

Investment   Interest Rates

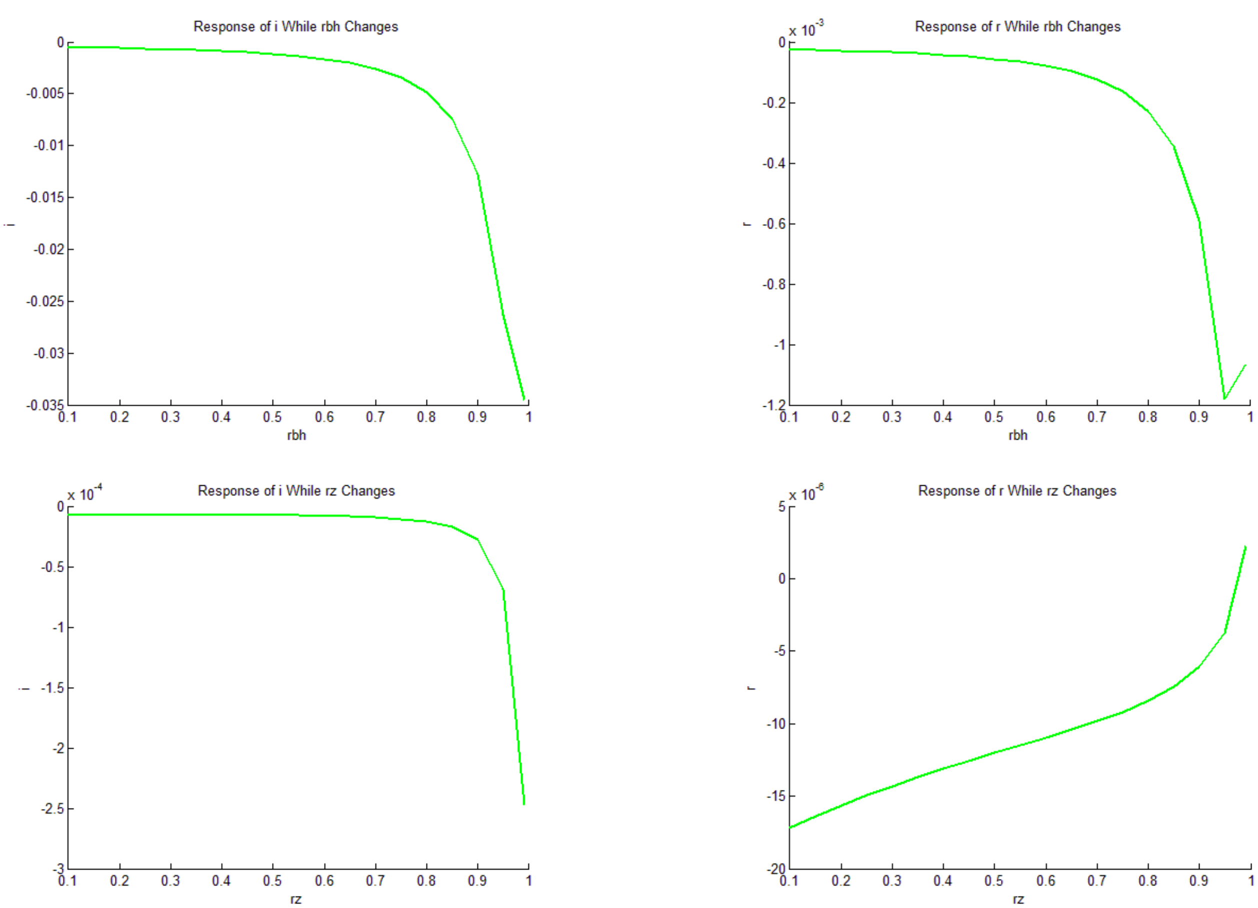


Figure 24: Differential responses of investment and interest rates while varying the persistence of shocks, for a second moment consumer preference shock (top), a second moment technology shock (bottom). Baseline calibration is used.

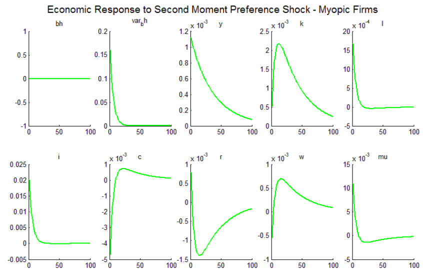


Figure 25: Impulse Response Functions for Consumer Preference Shocks With Myopic Firms. Note that the demand shock is now expansionary.

Part V

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10 Appendix

A - Quotes related to Buffet's Hypothesis (See Introduction)

"The principal cause of the economic slowdown was the collapse of the global credit boom and the ensuing financial crisis, which has affected asset values, credit conditions, and *consumer and business confidence* around the world. The immediate trigger of the crisis was the end of housing booms in the United States and other countries and the associated problems in mortgage markets, notably the collapse of the U.S. subprime mortgage market."

- Ben Bernake, Semiannual Monetary Report to Congress

"Right now, our economy is trapped in a *vicious cycle*: the turmoil on Wall Street means a new round of belt-tightening for families and businesses on Main Street... these extraordinary stresses on our financial system require extraordinary policy responses."

- Barack Obama, Speech (2009)

Graeme Leach, Chief Economist at IoD said: "Business is battening down the hatches in the expectation that the recession will continue for the rest of the year. "That is bad news for the economy at large, because decisions to invest money or take on more staff are being postponed until things look up. He commented that the combination of low economic confidence and delayed business decisions created a "*vicious cycle*".

- Miranda Dobson, Business Daily

"While you can't talk a strong economy into a weak one, *maybe we're making things worse by focusing on the negative news*. You can't escape the R-word these days. The question of whether the U.S. is in a recession - or in the process of sliding into one - dominates economic analysis and financial reporting, as well as conversations at work and around the kitchen table."

- Chris Farrell, Bloomberg Business Week

B - Regression of Jobs on Newspaper Penetration

As explained in the identification section, employment and APP may be correlated if employment is correlated with newspaper penetration. We might expect, for example, that more people subscribe to newspapers when times are good. The above regression estimates the effects of employment on newspaper penetration, controlling for a number of observables and using county and state-by-quarter fixed effects.

Table 21: Effects of Employment on Newspaper Penetration

	(1) Cnty, St*Qtr
Total Employment Per Person	0.01967***
	(0.000)
Pct. Hispanic	-0.33889***
	(0.000)
Pct. White	-0.73187***
	(0.000)
Pct. Black	-0.99587***
	(0.000)
Pct. Asian	-1.76930***
	(0.000)
Population	-0.00000***
	(0.000)
Pop. Density (Persons/Sq. Mi)	-0.00006***
	(0.000)
Pct. Some HS	-0.00004
	(0.997)
Pct. Comp. HS	0.06264***
	(0.000)
Pct. Some College	0.09831***
	(0.000)
Pct. Comp. College	-0.05844***
	(0.000)
Med. HH Income (Thousands)	-0.00027**
	(0.027)
Observations	86655
R^2	0.982
F	1.1e+03

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

C - Full Tables with All Covariates

The tables below display the full versions of regressions of APP and APR on various measures of employment (tables **??** through 12). These show point estimates for the demographic controls and the interactions between sectoral composition and national GDP, in addition to the estimates for the effects of news which are included in the smaller version. For a detailed explanation of why these covariates were chosen, please see the identification section.

Table 22: Effects of Pessimistic News on Total Employment

	(1) OLS	(2) Cnty, Qtr	(3) Cnty, Qtr	(4) Cnty, St*Qtr	(5) Cnty, Qtr	(6) Cnty, St*Qtr
Articles per Person	-0.00914***	-0.00127**				
	(0.000)	(0.049)				
(1st lag)	-0.00146	0.00019				
	(0.150)	(0.794)				
APP, No local/jobs			-0.00417***	-0.00207		
			(0.000)	(0.151)		
(1st lag)			0.00163	-0.00166		
			(0.201)	(0.286)		
No Local/Jobs, Natl					-0.04291***	-0.01465
					(0.001)	(0.304)
(1st lag)					0.00252	0.01410
					(0.856)	(0.348)
Pct. Hispanic	0.00717*	0.36753**	0.36799**	0.28325***	0.36928**	0.28247***
	(0.092)	(0.022)	(0.022)	(0.000)	(0.021)	(0.000)
Pct. White	-0.04812***	-1.28971***	-1.28754***	0.59422**	-1.26441***	0.58813**
	(0.000)	(0.005)	(0.005)	(0.024)	(0.006)	(0.026)
Pct. Black	-0.07702***	-1.71781***	-1.71706***	-0.09732	-1.69267***	-0.10600
	(0.000)	(0.001)	(0.001)	(0.724)	(0.001)	(0.701)
Pct. Asian	0.13754***	-2.08591***	-2.06294***	1.14163***	-2.01674***	1.06410***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Population	0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pop. Density (Persons/Sq. Mi)	-0.00001***	-0.00001	-0.00001	0.00001	-0.00000	0.00000
	(0.000)	(0.761)	(0.776)	(0.548)	(0.889)	(0.850)
Pct. Some HS	-0.07415***	0.07148	0.07163	0.03281	0.07474	0.03201
	(0.000)	(0.429)	(0.428)	(0.282)	(0.408)	(0.294)

Pct. Comp. HS	-0.17998***	0.00196	0.00193	0.04906**	0.00201	0.04969**
	(0.000)	(0.974)	(0.974)	(0.033)	(0.973)	(0.031)
Pct. Some College	-0.05414***	0.05776	0.05762	0.01206	0.05455	0.01243
	(0.000)	(0.511)	(0.512)	(0.686)	(0.534)	(0.678)
Pct. Comp. College	0.18298***	0.08439	0.08445	0.06948*	0.08495	0.07006*
	(0.000)	(0.333)	(0.333)	(0.054)	(0.328)	(0.052)
Med. HH Income (Thousands)	-0.00135***	0.00714***	0.00714***	0.00560***	0.00710***	0.00560***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Newspaper Penetration	0.10038***	0.03193	0.03154	0.05185***	0.02835	0.05145***
	(0.000)	(0.226)	(0.232)	(0.000)	(0.286)	(0.000)
Sec*GDP NAICS11	0.00002***	0.00001	0.00001	0.00005	0.00001	0.00005
	(0.000)	(0.909)	(0.916)	(0.525)	(0.899)	(0.520)
Sec*GDP NAICS21	0.00001***	0.00061***	0.00061***	0.00062***	0.00061***	0.00062***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sec*GDP NAICS22	0.00004***	-0.00026*	-0.00026*	-0.00030***	-0.00026*	-0.00030***
	(0.000)	(0.090)	(0.091)	(0.000)	(0.092)	(0.000)
Sec*GDP NAICS23	0.00004***	0.00024	0.00024	0.00031***	0.00024	0.00031***
	(0.000)	(0.116)	(0.116)	(0.000)	(0.129)	(0.000)
Sec*GDP NAICS42	0.00005***	0.00033**	0.00033**	0.00008	0.00033**	0.00009
	(0.000)	(0.036)	(0.037)	(0.207)	(0.037)	(0.184)
Sec*GDP NAICS44	0.00026***	-0.00001	-0.00001	0.00008	-0.00001	0.00008
	(0.000)	(0.976)	(0.978)	(0.462)	(0.983)	(0.476)
Sec*GDP NAICS48	0.00003***	0.00026**	0.00026**	0.00027***	0.00026**	0.00027***
	(0.000)	(0.029)	(0.030)	(0.000)	(0.028)	(0.000)
Sec*GDP NAICS49	-0.00005***	0.00028	0.00028	0.00038***	0.00029	0.00038***
	(0.000)	(0.548)	(0.547)	(0.008)	(0.543)	(0.007)
Sec*GDP NAICS51	-0.00015***	-0.00116***	-0.00116***	-0.00105***	-0.00116***	-0.00104***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sec*GDP NAICS52	-0.00006***	-0.00017	-0.00018	-0.00045***	-0.00017	-0.00045***
	(0.000)	(0.473)	(0.467)	(0.000)	(0.477)	(0.000)
Sec*GDP NAICS53	-0.00017***	-0.00060	-0.00060	-0.00027	-0.00058	-0.00027
	(0.000)	(0.181)	(0.186)	(0.374)	(0.193)	(0.378)
Sec*GDP NAICS54	-0.00011***	0.00023***	0.00024***	0.00027*	0.00023***	0.00027*

	(0.000)	(0.001)	(0.001)	(0.070)	(0.001)	(0.068)
Sec*GDP NAICS55	-0.00015***	-0.00055**	-0.00055**	-0.00029**	-0.00056**	-0.00029**
	(0.000)	(0.023)	(0.024)	(0.013)	(0.023)	(0.011)
Sec*GDP NAICS56	-0.00007***	-0.00016	-0.00016	-0.00005	-0.00016	-0.00005
	(0.000)	(0.321)	(0.319)	(0.398)	(0.336)	(0.428)
Sec*GDP NAICS61	0.00002***	0.00001	0.00001	-0.00004	0.00001	-0.00004
	(0.000)	(0.848)	(0.854)	(0.249)	(0.839)	(0.265)
Sec*GDP NAICS62	0.00000**	0.00005	0.00005	0.00009***	0.00006	0.00009***
	(0.039)	(0.475)	(0.480)	(0.005)	(0.418)	(0.005)
Sec*GDP NAICS71	-0.00006***	-0.00007	-0.00007	-0.00009*	-0.00007	-0.00009*
	(0.000)	(0.565)	(0.565)	(0.067)	(0.541)	(0.070)
Sec*GDP NAICS72	-0.00008***	-0.00025***	-0.00025***	-0.00022***	-0.00024***	-0.00022***
	(0.000)	(0.006)	(0.006)	(0.000)	(0.009)	(0.000)
Sec*GDP NAICS81	0.00010***	-0.00051	-0.00050	0.00009	-0.00051	0.00009
	(0.000)	(0.138)	(0.140)	(0.537)	(0.137)	(0.531)
Sec*GDP NAICS92	-0.00002***	-0.00016*	-0.00016*	-0.00011***	-0.00016*	-0.00011***
	(0.000)	(0.071)	(0.071)	(0.002)	(0.078)	(0.002)
Sec*GDP NAICS99	0.00001***	-0.00028***	-0.00029***	-0.00025***	-0.00029***	-0.00025***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	86655	86655	86655	86655	86655	86655
R^2	0.889	0.966	0.966	0.970	0.966	0.970
F	1.9e+04	8.1e+02	8.1e+02	6.3e+02	8.2e+02	6.3e+02

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

Table 23: Effects of Pessimistic News on Total Employment

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Cnty, Qtr	Cnty, Qtr	Cnty, St*Qtr	Cnty, Qtr	Cnty, St*Qtr
Articles Per Reader	-0.00188***	-0.00002				
	(0.000)	(0.931)				
(1st lag)	-0.00099***	-0.00031*				
	(0.000)	(0.099)				
APR, No Local/Jobs			-0.00076**	-0.00074*		

			(0.036)	(0.074)		
(1st lag)			-0.00008	-0.00044		
			(0.827)	(0.340)		
No Local/Jobs, Natl					-0.00537***	-0.00360**
					(0.008)	(0.041)
(1st lag)					-0.00067	0.00119
					(0.617)	(0.459)
Pct. Hispanic	0.00811*	0.36861**	0.36903**	0.27728***	0.36911**	0.28559***
	(0.056)	(0.022)	(0.022)	(0.001)	(0.021)	(0.000)
Pct. White	-0.04908***	-1.29668***	-1.29744***	0.58991**	-1.27599***	0.58851**
	(0.000)	(0.004)	(0.004)	(0.025)	(0.005)	(0.026)
Pct. Black	-0.07723***	-1.71899***	-1.72343***	-0.09156	-1.69029***	-0.09082
	(0.000)	(0.001)	(0.001)	(0.740)	(0.001)	(0.742)
Pct. Asian	0.13668***	-2.13598***	-2.11563***	1.08684***	-2.11005***	1.04840***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Population	0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pop. Density (Persons/Sq. Mi)	-0.00001***	-0.00001	-0.00001	0.00001	-0.00001	0.00000
	(0.000)	(0.773)	(0.803)	(0.515)	(0.810)	(0.698)
Pct. Some HS	-0.08104***	0.07699	0.07718	0.04002	0.07787	0.03894
	(0.000)	(0.397)	(0.396)	(0.197)	(0.392)	(0.209)
Pct. Comp. HS	-0.17606***	0.00127	0.00191	0.05028**	0.00052	0.04942**
	(0.000)	(0.983)	(0.975)	(0.031)	(0.993)	(0.033)
Pct. Some College	-0.05148***	0.05876	0.05851	0.01375	0.05750	0.01340
	(0.000)	(0.505)	(0.507)	(0.647)	(0.513)	(0.655)
Pct. Comp. College	0.17646***	0.08767	0.08753	0.07264**	0.08619	0.07381**
	(0.000)	(0.316)	(0.317)	(0.044)	(0.323)	(0.041)
Med. HH Income (Thousands)	-0.00133***	0.00715***	0.00714***	0.00561***	0.00712***	0.00561***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Newspaper Penetration	0.08351***	0.03237	0.03266	0.05258***	0.03293	0.05087***
	(0.000)	(0.220)	(0.216)	(0.000)	(0.213)	(0.000)
Sec*GDP NAICS11	0.00002***	0.00001	0.00001	0.00005	0.00001	0.00005

	(0.000)	(0.906)	(0.914)	(0.522)	(0.900)	(0.519)
Sec*GDP NAICS21	0.00001***	0.00061***	0.00061***	0.00062***	0.00061***	0.00063***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sec*GDP NAICS22	0.00004***	-0.00026*	-0.00026*	-0.00030***	-0.00026*	-0.00030***
	(0.000)	(0.091)	(0.091)	(0.000)	(0.088)	(0.000)
Sec*GDP NAICS23	0.00004***	0.00025	0.00025	0.00031***	0.00024	0.00031***
	(0.000)	(0.113)	(0.113)	(0.000)	(0.116)	(0.000)
Sec*GDP NAICS42	0.00005***	0.00033**	0.00033**	0.00008	0.00032**	0.00008
	(0.000)	(0.037)	(0.039)	(0.230)	(0.040)	(0.219)
Sec*GDP NAICS44	0.00026***	-0.00001	-0.00001	0.00008	-0.00000	0.00008
	(0.000)	(0.967)	(0.969)	(0.477)	(0.991)	(0.472)
Sec*GDP NAICS48	0.00003***	0.00026**	0.00026**	0.00027***	0.00026**	0.00027***
	(0.000)	(0.028)	(0.028)	(0.000)	(0.028)	(0.000)
Sec*GDP NAICS49	-0.00005***	0.00028	0.00028	0.00038***	0.00028	0.00038***
	(0.000)	(0.548)	(0.548)	(0.008)	(0.546)	(0.008)
Sec*GDP NAICS51	-0.00015***	-0.00116***	-0.00116***	-0.00104***	-0.00116***	-0.00104***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sec*GDP NAICS52	-0.00006***	-0.00017	-0.00018	-0.00045***	-0.00017	-0.00045***
	(0.000)	(0.473)	(0.465)	(0.000)	(0.469)	(0.000)
Sec*GDP NAICS53	-0.00018***	-0.00061	-0.00060	-0.00027	-0.00060	-0.00027
	(0.000)	(0.177)	(0.182)	(0.375)	(0.179)	(0.367)
Sec*GDP NAICS54	-0.00011***	0.00024***	0.00024***	0.00027*	0.00024***	0.00027*
	(0.000)	(0.001)	(0.001)	(0.069)	(0.001)	(0.068)
Sec*GDP NAICS55	-0.00015***	-0.00055**	-0.00055**	-0.00028**	-0.00056**	-0.00029**
	(0.000)	(0.024)	(0.025)	(0.014)	(0.024)	(0.012)
Sec*GDP NAICS56	-0.00007***	-0.00016	-0.00016	-0.00005	-0.00016	-0.00005
	(0.000)	(0.328)	(0.326)	(0.429)	(0.343)	(0.456)
Sec*GDP NAICS61	0.00002***	0.00001	0.00001	-0.00004	0.00002	-0.00003
	(0.000)	(0.834)	(0.840)	(0.267)	(0.819)	(0.287)
Sec*GDP NAICS62	0.00001***	0.00005	0.00005	0.00009***	0.00005	0.00009***
	(0.005)	(0.461)	(0.466)	(0.004)	(0.437)	(0.004)
Sec*GDP NAICS71	-0.00006***	-0.00006	-0.00007	-0.00009*	-0.00007	-0.00009*

	(0.000)	(0.569)	(0.562)	(0.065)	(0.544)	(0.066)
Sec*GDP NAICS72	-0.00008***	-0.00025***	-0.00025***	-0.00022***	-0.00024***	-0.00021***
	(0.000)	(0.006)	(0.006)	(0.000)	(0.007)	(0.000)
Sec*GDP NAICS81	0.00010***	-0.00051	-0.00051	0.00008	-0.00051	0.00008
	(0.000)	(0.134)	(0.135)	(0.558)	(0.135)	(0.544)
Sec*GDP NAICS92	-0.00002***	-0.00016*	-0.00016*	-0.00011***	-0.00015*	-0.00011***
	(0.000)	(0.075)	(0.074)	(0.002)	(0.079)	(0.002)
Sec*GDP NAICS99	0.00001***	-0.00028***	-0.00028***	-0.00025***	-0.00028***	-0.00025***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	86565	86565	86565	86565	86565	86565
R^2	0.889	0.966	0.966	0.970	0.966	0.970
F	1.9e+04	8.1e+02	8.1e+02	6.3e+02	8.1e+02	6.3e+02

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

Table 24: Effects of Pessimistic News on Hiring

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Cnty, Qtr	Cnty, Qtr	Cnty, St*Qtr	Cnty, Qtr	Cnty, St*Qtr
Articles per Person	0.01678***	-0.00505***				
	(0.000)	(0.004)				
(1st lag)	-0.05832***	-0.00380**				
	(0.000)	(0.025)				
APP, No local/jobs			-0.00992***	-0.00811**		
			(0.001)	(0.030)		
(1st lag)			-0.00676**	-0.00507		
			(0.023)	(0.174)		
No Local/Jobs, Natl					-0.09832***	-0.02980
					(0.004)	(0.403)
(1st lag)					-0.04585	0.00223
					(0.215)	(0.952)
Pct. Hispanic	0.20508***	0.65581**	0.65648**	0.38527**	0.65850**	0.39006**
	(0.000)	(0.025)	(0.025)	(0.043)	(0.024)	(0.041)
Pct. White	-0.26905***	-2.40989***	-2.40768***	0.96477	-2.35172***	0.94616

	(0.000)	(0.003)	(0.003)	(0.183)	(0.004)	(0.191)
Pct. Black	-0.22035***	-2.53664***	-2.54283***	0.38781	-2.47452***	0.36053
	(0.000)	(0.004)	(0.004)	(0.602)	(0.005)	(0.628)
Pct. Asian	-0.09447**	-6.74724***	-6.68838***	0.61250	-6.72971***	0.40570
	(0.016)	(0.000)	(0.000)	(0.496)	(0.000)	(0.654)
Population	0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Pop. Density (Persons/Sq. Mi)	-0.00001***	0.00007*	0.00007*	0.00009***	0.00007*	0.00007**
	(0.000)	(0.066)	(0.069)	(0.008)	(0.091)	(0.027)
Pct. Some HS	0.33231***	-0.08361	-0.08234	-0.05301	-0.07129	-0.05410
	(0.000)	(0.549)	(0.555)	(0.454)	(0.610)	(0.445)
Pct. Comp. HS	-0.49159***	-0.17535	-0.17509	-0.15000**	-0.17520	-0.14789**
	(0.000)	(0.110)	(0.110)	(0.018)	(0.111)	(0.020)
Pct. Some College	0.22591***	0.00333	0.00377	-0.08966	-0.00558	-0.09082
	(0.000)	(0.981)	(0.978)	(0.237)	(0.968)	(0.231)
Pct. Comp. College	0.60896***	-0.18766	-0.18785	-0.17161*	-0.18649	-0.16886*
	(0.000)	(0.194)	(0.193)	(0.067)	(0.198)	(0.071)
Med. HH Income (Thousands)	-0.00019	0.01588***	0.01588***	0.01060***	0.01575***	0.01060***
	(0.355)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Newspaper Penetration	0.03744***	0.07154	0.06956	0.03326	0.05930	0.02919
	(0.000)	(0.132)	(0.142)	(0.321)	(0.218)	(0.385)
Sec*GDP NAICS11	0.00003***	-0.00011	-0.00011	-0.00004	-0.00010	-0.00003
	(0.000)	(0.499)	(0.497)	(0.789)	(0.538)	(0.805)
Sec*GDP NAICS21	0.00012***	0.00142***	0.00143***	0.00142***	0.00144***	0.00142***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sec*GDP NAICS22	-0.00004***	0.00099***	0.00099***	0.00080***	0.00100***	0.00079***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Sec*GDP NAICS23	0.00020***	0.00050*	0.00049*	0.00051***	0.00047*	0.00051***
	(0.000)	(0.056)	(0.056)	(0.007)	(0.071)	(0.008)
Sec*GDP NAICS42	0.00001	0.00053*	0.00052*	0.00013	0.00053*	0.00015
	(0.401)	(0.053)	(0.057)	(0.450)	(0.052)	(0.407)
Sec*GDP NAICS44	0.00042***	-0.00029	-0.00029	-0.00004	-0.00029	-0.00004

	(0.000)	(0.513)	(0.512)	(0.896)	(0.508)	(0.873)
Sec*GDP NAICS48	0.00016***	0.00028	0.00028	0.00025	0.00029	0.00025
	(0.000)	(0.177)	(0.183)	(0.106)	(0.175)	(0.107)
Sec*GDP NAICS49	-0.00002	0.00023	0.00023	0.00045	0.00025	0.00046
	(0.192)	(0.772)	(0.768)	(0.149)	(0.756)	(0.143)
Sec*GDP NAICS51	-0.00007***	-0.00124***	-0.00123***	-0.00092***	-0.00117***	-0.00087***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Sec*GDP NAICS52	-0.00011***	-0.00011	-0.00012	-0.00053**	-0.00009	-0.00052**
	(0.000)	(0.749)	(0.737)	(0.032)	(0.789)	(0.035)
Sec*GDP NAICS53	0.00014***	-0.00165**	-0.00163**	-0.00151*	-0.00156**	-0.00151*
	(0.000)	(0.043)	(0.046)	(0.094)	(0.050)	(0.094)
Sec*GDP NAICS54	-0.00007***	-0.00007	-0.00007	0.00002	-0.00006	0.00002
	(0.000)	(0.510)	(0.511)	(0.856)	(0.537)	(0.824)
Sec*GDP NAICS55	-0.00005***	-0.00036	-0.00036	0.00032	-0.00040	0.00030
	(0.001)	(0.291)	(0.290)	(0.216)	(0.253)	(0.251)
Sec*GDP NAICS56	0.00002***	-0.00012	-0.00013	-0.00005	-0.00011	-0.00004
	(0.003)	(0.453)	(0.444)	(0.700)	(0.511)	(0.756)
Sec*GDP NAICS61	0.00002***	0.00017	0.00017	0.00013	0.00018	0.00013
	(0.000)	(0.196)	(0.199)	(0.254)	(0.184)	(0.238)
Sec*GDP NAICS62	0.00004***	-0.00004	-0.00004	-0.00002	-0.00002	-0.00002
	(0.000)	(0.726)	(0.735)	(0.826)	(0.866)	(0.844)
Sec*GDP NAICS71	-0.00001	-0.00013	-0.00012	-0.00013	-0.00013	-0.00013
	(0.325)	(0.413)	(0.417)	(0.369)	(0.399)	(0.370)
Sec*GDP NAICS72	-0.00003***	-0.00075***	-0.00075***	-0.00056***	-0.00071***	-0.00055***
	(0.000)	(0.006)	(0.006)	(0.002)	(0.009)	(0.002)
Sec*GDP NAICS81	0.00003*	-0.00196***	-0.00196***	-0.00015	-0.00197***	-0.00015
	(0.058)	(0.005)	(0.005)	(0.659)	(0.004)	(0.664)
Sec*GDP NAICS92	-0.00004***	-0.00016	-0.00016	-0.00000	-0.00015	-0.00000
	(0.000)	(0.300)	(0.303)	(0.999)	(0.341)	(0.988)
Sec*GDP NAICS99	-0.00002***	-0.00038***	-0.00038***	-0.00033***	-0.00038***	-0.00033***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	85755	85755	85755	85755	85755	85755
R^2	0.642	0.828	0.828	0.849	0.828	0.849

F	4.2e+03	1.3e+02	1.3e+02	1.1e+02	1.3e+02	1.1e+02

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. Hiring refers to new stable hires, defined as total number of workers who were new hires by the employer in the last quarter and are full-quarter employed in the current quarter.

Table 25: Effects of Pessimistic News on Hiring

	(1) OLS	(2) Cnty, Qtr	(3) Cnty, Qtr	(4) Cnty, St*Qtr	(5) Cnty, Qtr	(6) Cnty, St*Qtr
Articles Per Reader	0.00534***	-0.00163***				
	(0.000)	(0.001)				
(1st lag)	-0.01507***	-0.00035				
	(0.000)	(0.438)				
APR, No Local/Jobs			-0.00282***	-0.00278***		
			(0.001)	(0.006)		
(1st lag)			-0.00101	-0.00029		
			(0.259)	(0.811)		
No Local/Jobs, Natl					-0.01614***	-0.00762**
					(0.000)	(0.028)
(1st lag)					-0.00187	0.00167
					(0.587)	(0.685)
Pct. Hispanic	0.20590***	0.66309**	0.66010**	0.36587*	0.65613**	0.38823**
	(0.000)	(0.024)	(0.024)	(0.054)	(0.025)	(0.042)
Pct. White	-0.26989***	-2.46100***	-2.46407***	0.94272	-2.40450***	0.93694
	(0.000)	(0.002)	(0.002)	(0.193)	(0.003)	(0.196)
Pct. Black	-0.21930***	-2.57792***	-2.59465***	0.39573	-2.49018***	0.39527
	(0.000)	(0.003)	(0.003)	(0.595)	(0.005)	(0.595)
Pct. Asian	-0.09717**	-7.03732***	-7.00522***	0.37913	-7.07648***	0.27336
	(0.013)	(0.000)	(0.000)	(0.674)	(0.000)	(0.762)
Population	0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Pop. Density (Persons/Sq. Mi)	-0.00001***	0.00006	0.00006	0.00008**	0.00006	0.00007**
	(0.000)	(0.123)	(0.117)	(0.013)	(0.198)	(0.025)

Pct. Some HS	0.30455***	-0.07670	-0.07485	-0.03585	-0.07195	-0.03818
	(0.000)	(0.584)	(0.593)	(0.614)	(0.609)	(0.591)
Pct. Comp. HS	-0.48205***	-0.17589	-0.17366	-0.14811**	-0.17931	-0.14959**
	(0.000)	(0.108)	(0.112)	(0.020)	(0.104)	(0.019)
Pct. Some College	0.23133***	0.00527	0.00559	-0.08544	0.00457	-0.08594
	(0.000)	(0.970)	(0.968)	(0.262)	(0.974)	(0.258)
Pct. Comp. College	0.57208***	-0.18196	-0.18219	-0.16026*	-0.18529	-0.15724*
	(0.000)	(0.208)	(0.208)	(0.086)	(0.201)	(0.092)
Med. HH Income (Thousands)	-0.00024	0.01588***	0.01588***	0.01061***	0.01583***	0.01060***
	(0.235)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Newspaper Penetration	-0.02268***	0.07828	0.07812	0.03518	0.07730	0.03065
	(0.001)	(0.102)	(0.103)	(0.292)	(0.108)	(0.361)
Sec*GDP NAICS11	0.00003***	-0.00011	-0.00011	-0.00004	-0.00010	-0.00003
	(0.000)	(0.505)	(0.505)	(0.789)	(0.543)	(0.802)
Sec*GDP NAICS21	0.00013***	0.00143***	0.00143***	0.00142***	0.00145***	0.00143***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sec*GDP NAICS22	-0.00005***	0.00098***	0.00099***	0.00079***	0.00098***	0.00079***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Sec*GDP NAICS23	0.00020***	0.00051*	0.00050*	0.00052***	0.00049*	0.00051***
	(0.000)	(0.051)	(0.052)	(0.006)	(0.056)	(0.007)
Sec*GDP NAICS42	0.00001	0.00053*	0.00052*	0.00014	0.00052*	0.00015
	(0.340)	(0.051)	(0.055)	(0.425)	(0.053)	(0.404)
Sec*GDP NAICS44	0.00042***	-0.00028	-0.00029	-0.00003	-0.00027	-0.00003
	(0.000)	(0.519)	(0.514)	(0.906)	(0.530)	(0.905)
Sec*GDP NAICS48	0.00015***	0.00028	0.00028	0.00025	0.00028	0.00025
	(0.000)	(0.178)	(0.184)	(0.103)	(0.182)	(0.104)
Sec*GDP NAICS49	-0.00002	0.00024	0.00024	0.00046	0.00025	0.00046
	(0.199)	(0.767)	(0.763)	(0.149)	(0.757)	(0.145)
Sec*GDP NAICS51	-0.00008***	-0.00118***	-0.00117***	-0.00088***	-0.00116***	-0.00087***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Sec*GDP NAICS52	-0.00011***	-0.00010	-0.00011	-0.00052**	-0.00009	-0.00051**
	(0.000)	(0.764)	(0.754)	(0.034)	(0.792)	(0.036)
Sec*GDP NAICS53	0.00012***	-0.00163**	-0.00161**	-0.00152*	-0.00162**	-0.00154*

	(0.000)	(0.044)	(0.046)	(0.093)	(0.039)	(0.088)
Sec*GDP NAICS54	-0.00007***	-0.00006	-0.00006	0.00002	-0.00006	0.00002
	(0.000)	(0.530)	(0.528)	(0.852)	(0.552)	(0.830)
Sec*GDP NAICS55	-0.00006***	-0.00036	-0.00036	0.00032	-0.00040	0.00030
	(0.000)	(0.296)	(0.293)	(0.224)	(0.255)	(0.252)
Sec*GDP NAICS56	0.00002***	-0.00012	-0.00012	-0.00005	-0.00010	-0.00004
	(0.001)	(0.476)	(0.471)	(0.731)	(0.529)	(0.773)
Sec*GDP NAICS61	0.00002***	0.00018	0.00018	0.00013	0.00019	0.00014
	(0.000)	(0.179)	(0.182)	(0.230)	(0.169)	(0.218)
Sec*GDP NAICS62	0.00004***	-0.00004	-0.00004	-0.00002	-0.00003	-0.00002
	(0.000)	(0.712)	(0.723)	(0.809)	(0.800)	(0.839)
Sec*GDP NAICS71	-0.00001	-0.00012	-0.00012	-0.00013	-0.00013	-0.00013
	(0.234)	(0.419)	(0.418)	(0.364)	(0.388)	(0.365)
Sec*GDP NAICS72	-0.00003***	-0.00074***	-0.00074***	-0.00055***	-0.00070***	-0.00054***
	(0.000)	(0.006)	(0.006)	(0.002)	(0.008)	(0.003)
Sec*GDP NAICS81	0.00003**	-0.00197***	-0.00198***	-0.00017	-0.00198***	-0.00016
	(0.042)	(0.004)	(0.004)	(0.622)	(0.004)	(0.628)
Sec*GDP NAICS92	-0.00005***	-0.00016	-0.00016	-0.00000	-0.00015	0.00000
	(0.000)	(0.301)	(0.299)	(1.000)	(0.332)	(0.990)
Sec*GDP NAICS99	-0.00002***	-0.00038***	-0.00038***	-0.00033***	-0.00038***	-0.00032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	85665	85665	85665	85665	85665	85665
R^2	0.642	0.828	0.828	0.849	0.828	0.849
F	4.1e+03	1.3e+02	1.3e+02	1.1e+02	1.3e+02	1.1e+02

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. Hiring refers to new stable hires, defined as total number of workers who were new hires by the employer in the last quarter and are full-quarter employed in the current quarter.

Table 26: Effects of Pessimistic News on Separations

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Cnty, Qtr	Cnty, Qtr	Cnty, St*Qtr	Cnty, Qtr	Cnty, St*Qtr
Articles per Person	-0.02008***	-0.00045				
	(0.000)	(0.828)				

(1st lag)	0.00557**	-0.00424*				
	(0.017)	(0.059)				
APP, No local/jobs			-0.01028***	0.00202		
			(0.003)	(0.655)		
(1st lag)			0.00137	-0.00914**		
			(0.708)	(0.025)		
No Local/Jobs, Natl					0.09950***	0.00621
					(0.001)	(0.871)
(1st lag)					-0.16935***	-0.04368
					(0.000)	(0.298)
Pct. Hispanic	0.12381***	-0.29944	-0.29816	0.18053	-0.29647	0.19017
	(0.000)	(0.232)	(0.234)	(0.423)	(0.236)	(0.399)
Pct. White	-0.26540***	-1.37592**	-1.37454**	1.19830	-1.35690**	1.19302
	(0.000)	(0.033)	(0.033)	(0.126)	(0.035)	(0.128)
Pct. Black	-0.15654***	-2.11321***	-2.11576***	0.24191	-2.08381***	0.23286
	(0.000)	(0.003)	(0.003)	(0.768)	(0.003)	(0.777)
Pct. Asian	-0.27493***	-3.52428***	-3.48824***	1.07960	-3.49983***	1.03767
	(0.000)	(0.000)	(0.000)	(0.308)	(0.000)	(0.327)
Population	0.00000***	-0.00000***	-0.00000***	-0.00000**	-0.00000***	-0.00000**
	(0.001)	(0.008)	(0.008)	(0.028)	(0.007)	(0.026)
Pop. Density (Persons/Sq. Mi)	-0.00001***	-0.00011***	-0.00011***	-0.00006*	-0.00011***	-0.00006*
	(0.000)	(0.001)	(0.001)	(0.100)	(0.002)	(0.089)
Pct. Some HS	0.35874***	0.21559*	0.21596*	0.09818	0.22317*	0.09941
	(0.000)	(0.069)	(0.068)	(0.301)	(0.059)	(0.294)
Pct. Comp. HS	-0.22003***	-0.23270***	-0.23275***	-0.13937*	-0.23224***	-0.13832*
	(0.000)	(0.010)	(0.010)	(0.086)	(0.010)	(0.088)
Pct. Some College	0.25758***	-0.07198	-0.07194	-0.13071	-0.07686	-0.13313
	(0.000)	(0.543)	(0.544)	(0.172)	(0.515)	(0.165)
Pct. Comp. College	0.68236***	-0.01176	-0.01189	-0.01172	-0.01002	-0.00912
	(0.000)	(0.924)	(0.923)	(0.911)	(0.935)	(0.931)
Med. HH Income (Thousands)	-0.00242***	0.00636***	0.00637***	0.00511***	0.00630***	0.00510***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Newspaper Penetration	0.08780***	-0.01426	-0.01517	0.09798***	-0.02247	0.09317**

	(0.000)	(0.758)	(0.743)	(0.008)	(0.628)	(0.012)
Sec*GDP NAICS11	0.00004***	0.00024*	0.00024*	0.00013	0.00024*	0.00013
	(0.000)	(0.070)	(0.073)	(0.437)	(0.065)	(0.435)
Sec*GDP NAICS21	0.00005***	0.00068**	0.00068**	0.00076***	0.00069**	0.00076***
	(0.000)	(0.020)	(0.021)	(0.000)	(0.019)	(0.000)
Sec*GDP NAICS22	-0.00007***	-0.00004	-0.00004	-0.00019	-0.00003	-0.00019
	(0.000)	(0.900)	(0.907)	(0.501)	(0.918)	(0.500)
Sec*GDP NAICS23	0.00017***	0.00070***	0.00070***	0.00053***	0.00069***	0.00052***
	(0.000)	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)
Sec*GDP NAICS42	-0.00003***	0.00044*	0.00044*	-0.00004	0.00045*	-0.00003
	(0.003)	(0.080)	(0.084)	(0.851)	(0.077)	(0.869)
Sec*GDP NAICS44	0.00039***	-0.00034	-0.00034	-0.00006	-0.00035	-0.00006
	(0.000)	(0.328)	(0.329)	(0.846)	(0.316)	(0.843)
Sec*GDP NAICS48	0.00008***	0.00014	0.00014	0.00016	0.00014	0.00017
	(0.000)	(0.617)	(0.618)	(0.491)	(0.622)	(0.488)
Sec*GDP NAICS49	-0.00002	0.00032	0.00033	0.00026	0.00032	0.00027
	(0.219)	(0.601)	(0.597)	(0.399)	(0.602)	(0.393)
Sec*GDP NAICS51	-0.00009***	-0.00092***	-0.00089***	-0.00085***	-0.00091***	-0.00082***
	(0.000)	(0.004)	(0.005)	(0.007)	(0.004)	(0.009)
Sec*GDP NAICS52	-0.00013***	0.00017	0.00017	-0.00025	0.00018	-0.00024
	(0.000)	(0.524)	(0.536)	(0.243)	(0.513)	(0.244)
Sec*GDP NAICS53	0.00026***	-0.00003	0.00000	0.00038	-0.00001	0.00039
	(0.000)	(0.956)	(0.998)	(0.640)	(0.987)	(0.637)
Sec*GDP NAICS54	-0.00010***	0.00008	0.00008	0.00010	0.00008	0.00010
	(0.000)	(0.341)	(0.325)	(0.433)	(0.332)	(0.423)
Sec*GDP NAICS55	-0.00008***	-0.00116**	-0.00115**	-0.00087**	-0.00118***	-0.00088***
	(0.000)	(0.012)	(0.013)	(0.010)	(0.010)	(0.009)
Sec*GDP NAICS56	-0.00003***	-0.00013	-0.00013	0.00009	-0.00013	0.00010
	(0.000)	(0.560)	(0.555)	(0.570)	(0.561)	(0.550)
Sec*GDP NAICS61	0.00001***	0.00006	0.00006	-0.00003	0.00006	-0.00003
	(0.005)	(0.562)	(0.568)	(0.779)	(0.555)	(0.791)
Sec*GDP NAICS62	0.00000	-0.00018*	-0.00018*	-0.00005	-0.00017*	-0.00004

	(0.625)	(0.087)	(0.082)	(0.668)	(0.098)	(0.680)
Sec*GDP NAICS71	-0.00002***	-0.00021	-0.00021	-0.00034*	-0.00021	-0.00034*
	(0.001)	(0.288)	(0.291)	(0.052)	(0.290)	(0.051)
Sec*GDP NAICS72	-0.00003***	-0.00020	-0.00020	-0.00025*	-0.00020	-0.00024*
	(0.000)	(0.103)	(0.102)	(0.083)	(0.112)	(0.091)
Sec*GDP NAICS81	0.00006***	-0.00048	-0.00046	-0.00027	-0.00049	-0.00026
	(0.000)	(0.297)	(0.311)	(0.427)	(0.281)	(0.446)
Sec*GDP NAICS92	-0.00004***	-0.00027**	-0.00027**	-0.00022**	-0.00027**	-0.00022**
	(0.000)	(0.034)	(0.033)	(0.039)	(0.035)	(0.039)
Sec*GDP NAICS99	-0.00001***	-0.00008	-0.00008	-0.00016**	-0.00008	-0.00016**
	(0.000)	(0.364)	(0.354)	(0.026)	(0.358)	(0.026)
Observations	86370	86370	86370	86370	86370	86370
R^2	0.604	0.759	0.759	0.799	0.759	0.799
F	3.6e+03	88.72697	88.73107	75.94878	88.75585	75.94430

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. Separations refers to separations from stable employment, defined as the total number of workers who are employed for the entire previous quarter at some employer but are not employed at that employer in the current quarter.

Table 27: Effects of Pessimistic News on Separations

	(1) OLS	(2) Cnty, Qtr	(3) Cnty, Qtr	(4) Cnty, St*Qtr	(5) Cnty, Qtr	(6) Cnty, St*Qtr
Articles Per Reader	-0.00429***	0.00077				
	(0.000)	(0.195)				
(1st lag)	0.00035	-0.00207***				
	(0.539)	(0.001)				
APR, No Local/Jobs			-0.00146	0.00098		
			(0.154)	(0.421)		
(1st lag)			-0.00107	-0.00279**		
			(0.298)	(0.011)		
No Local/Jobs, Natl					0.00441	-0.00025
					(0.281)	(0.943)
(1st lag)					-0.01202***	-0.00273
					(0.009)	(0.439)

Pct. Hispanic	0.12531***	-0.29707	-0.29784	0.17013	-0.30186	0.18182
	(0.000)	(0.236)	(0.234)	(0.450)	(0.228)	(0.421)
Pct. White	-0.26607***	-1.39678**	-1.40379**	1.18930	-1.38367**	1.18452
	(0.000)	(0.031)	(0.030)	(0.129)	(0.032)	(0.131)
Pct. Black	-0.15433***	-2.15288***	-2.16704***	0.22838	-2.11753***	0.22785
	(0.000)	(0.002)	(0.002)	(0.781)	(0.003)	(0.782)
Pct. Asian	-0.27553***	-3.63995***	-3.61601***	0.96171	-3.70087***	0.90861
	(0.000)	(0.000)	(0.000)	(0.362)	(0.000)	(0.388)
Population	0.00000***	-0.00000***	-0.00000***	-0.00000**	-0.00000***	-0.00000**
	(0.001)	(0.009)	(0.009)	(0.028)	(0.008)	(0.026)
Pop. Density (Persons/Sq. Mi)	-0.00001***	-0.00011***	-0.00011***	-0.00006*	-0.00012***	-0.00007*
	(0.000)	(0.001)	(0.001)	(0.095)	(0.000)	(0.066)
Pct. Some HS	0.33912***	0.22142*	0.22207*	0.10979	0.22391*	0.10817
	(0.000)	(0.062)	(0.061)	(0.250)	(0.060)	(0.256)
Pct. Comp. HS	-0.22020***	-0.23993***	-0.23892***	-0.14437*	-0.24259***	-0.14562*
	(0.000)	(0.008)	(0.008)	(0.076)	(0.007)	(0.073)
Pct. Some College	0.25383***	-0.07642	-0.07663	-0.13295	-0.07591	-0.13328
	(0.000)	(0.518)	(0.517)	(0.165)	(0.520)	(0.164)
Pct. Comp. College	0.66580***	-0.01574	-0.01601	-0.01276	-0.01661	-0.01044
	(0.000)	(0.898)	(0.896)	(0.903)	(0.892)	(0.920)
Med. HH Income (Thousands)	-0.00239***	0.00636***	0.00636***	0.00513***	0.00635***	0.00512***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Newspaper Penetration	0.06416***	-0.00957	-0.00919	0.09945***	-0.01080	0.09670***
	(0.000)	(0.835)	(0.842)	(0.007)	(0.815)	(0.009)
Sec*GDP NAICS11	0.00004***	0.00024*	0.00024*	0.00013	0.00024*	0.00013
	(0.000)	(0.068)	(0.070)	(0.429)	(0.063)	(0.430)
Sec*GDP NAICS21	0.00005***	0.00068**	0.00068**	0.00076***	0.00069**	0.00076***
	(0.000)	(0.020)	(0.020)	(0.000)	(0.018)	(0.000)
Sec*GDP NAICS22	-0.00007***	-0.00004	-0.00004	-0.00019	-0.00004	-0.00019
	(0.000)	(0.894)	(0.896)	(0.502)	(0.904)	(0.502)
Sec*GDP NAICS23	0.00017***	0.00071***	0.00071***	0.00053***	0.00070***	0.00053***
	(0.000)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
Sec*GDP NAICS42	-0.00003***	0.00044*	0.00044*	-0.00004	0.00044*	-0.00004

	(0.003)	(0.079)	(0.085)	(0.842)	(0.080)	(0.853)
Sec*GDP NAICS44	0.00039***	-0.00035	-0.00035	-0.00006	-0.00035	-0.00006
	(0.000)	(0.324)	(0.322)	(0.836)	(0.319)	(0.832)
Sec*GDP NAICS48	0.00008***	0.00015	0.00014	0.00017	0.00014	0.00017
	(0.000)	(0.613)	(0.615)	(0.472)	(0.617)	(0.474)
Sec*GDP NAICS49	-0.00002	0.00033	0.00033	0.00027	0.00033	0.00027
	(0.215)	(0.595)	(0.592)	(0.393)	(0.593)	(0.393)
Sec*GDP NAICS51	-0.00009***	-0.00090***	-0.00088***	-0.00082***	-0.00087***	-0.00081**
	(0.000)	(0.005)	(0.006)	(0.010)	(0.006)	(0.011)
Sec*GDP NAICS52	-0.00013***	0.00017	0.00017	-0.00025	0.00018	-0.00024
	(0.000)	(0.518)	(0.535)	(0.244)	(0.498)	(0.244)
Sec*GDP NAICS53	0.00025***	-0.00003	0.00000	0.00039	0.00001	0.00039
	(0.000)	(0.965)	(0.997)	(0.638)	(0.990)	(0.637)
Sec*GDP NAICS54	-0.00010***	0.00008	0.00008	0.00010	0.00009	0.00011
	(0.000)	(0.328)	(0.323)	(0.421)	(0.308)	(0.415)
Sec*GDP NAICS55	-0.00008***	-0.00115**	-0.00115**	-0.00086**	-0.00117**	-0.00087***
	(0.000)	(0.012)	(0.013)	(0.010)	(0.011)	(0.010)
Sec*GDP NAICS56	-0.00002***	-0.00013	-0.00013	0.00010	-0.00012	0.00010
	(0.000)	(0.576)	(0.569)	(0.534)	(0.583)	(0.525)
Sec*GDP NAICS61	0.00001***	0.00006	0.00006	-0.00003	0.00006	-0.00003
	(0.005)	(0.550)	(0.555)	(0.801)	(0.534)	(0.809)
Sec*GDP NAICS62	0.00000	-0.00018*	-0.00018*	-0.00004	-0.00018*	-0.00004
	(0.370)	(0.089)	(0.087)	(0.679)	(0.096)	(0.676)
Sec*GDP NAICS71	-0.00002***	-0.00021	-0.00021	-0.00034*	-0.00020	-0.00034*
	(0.001)	(0.290)	(0.285)	(0.052)	(0.297)	(0.053)
Sec*GDP NAICS72	-0.00003***	-0.00020	-0.00020	-0.00024*	-0.00019	-0.00024*
	(0.000)	(0.107)	(0.106)	(0.087)	(0.121)	(0.090)
Sec*GDP NAICS81	0.00006***	-0.00049	-0.00048	-0.00029	-0.00049	-0.00028
	(0.000)	(0.282)	(0.290)	(0.403)	(0.284)	(0.422)
Sec*GDP NAICS92	-0.00004***	-0.00027**	-0.00027**	-0.00022**	-0.00027**	-0.00022**
	(0.000)	(0.036)	(0.034)	(0.043)	(0.037)	(0.042)
Sec*GDP NAICS99	-0.00001***	-0.00008	-0.00008	-0.00015**	-0.00008	-0.00015**

	(0.000)	(0.372)	(0.359)	(0.030)	(0.384)	(0.030)
Observations	86280	86280	86280	86280	86280	86280
R^2	0.604	0.759	0.759	0.799	0.759	0.799
F	3.6e+03	88.67725	88.66848	75.87301	88.66694	75.86339

1. P-values in parentheses. * p<0.1, ** p<0.05, *** p<0.01

2. Column names denote fixed effects specification, for example, columns (4) and (6) include county and state by quarter fixed effects.

3. Standard error clustered at county level for colums (2), (3), and (5); at state-by-quarter level for (4), (6).

4. Separations refers to separations from stable employment, defined as the total number of workers who are employed for the entire previous quarter at some employer but are not employed at that employer in the current quarter.