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# Essays on Innovation and Consumer Credit

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A thesis submitted in partial fulfillment of the requirements for the degree in Doctor of Philosophy

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# ESSAYS ON INNOVATION AND CONSUMER CREDIT

(Thesis format: Integrated Article)

by

David Fieldhouse

Graduate Program in Economics

SUBMITTED IN PARTIAL FULFILLMENT OF THE  
REQUIREMENTS FOR THE DEGREE OF  
DOCTOR OF PHILOSOPHY

SCHOOL OF GRADUATE AND POSTDOCTORAL STUDIES  
THE UNIVERSITY OF WESTERN ONTARIO  
LONDON, CANADA  
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# Abstract

This thesis consists of three chapters on Innovation and Consumer Credit. In Chapter 2, I examine the relationship between the number and quality of patents at both the aggregate and industry level. I find a negative relationship at the aggregate level that, surprisingly, vanishes at the industry level. I reconcile the aggregate and industry relationships by considering interactions between industries. The average correlation between the number of patents in one industry and the quality of patents in another industry turns out to be negative. I propose that the inter-industry relationship results from the outputs of each industry being complements in the production of goods. When the quality of available ideas improves in one industry, the output of that industry will increase, which leads to increased demand in the complementary industry. This increases the returns from inventing in the second industry, and results in their inventors developing ideas below the prior quality threshold. I develop a multi-industry innovation model to capture this mechanism. I also provide evidence that the inter-industry relationship strengthens with a measure of complementarities between any two industries.

These findings suggest that production complementarities between industries are an important determinant of innovation, which had not been previously considered. They also contribute to the current debate on U.S. patent policy, where there is a growing belief among scholars and practitioners that the quality of patents has declined during their recent surge in number. This viewpoint largely attributes the surge in patents to their increased value in

detering competition. Instead, I use the model to demonstrate that such a decline could be explained by increased innovative opportunities in certain industries and the corresponding response of complementary industries.

Chapter 3 investigates the key factors driving cyclical fluctuations in Canadian consumer insolvency filings, with a focus on the 2008-09 recession where insolvencies jumped by nearly 50%. Our analysis uses historical data at the national, provincial and city levels, as well as a micro-level analysis which makes use of filer-level data from a unique dataset of Canadian insolvency filers from 2005-11. We find that the direct effect of adverse income shocks (unemployment) accounts for roughly half the cyclical volatility of filings, while shifts in “lending standards” account for roughly a quarter. We also document an increase in the share of filers with “middle-class” characteristics during the recession – a larger fraction of filers are homeowners, live with a spouse or a partner, have student loans, earn larger incomes and are middle-aged. Furthermore, the average outstanding total debt of filers is larger during the recession, suggesting that either income shocks are hitting middle-class individuals disproportionately more, or that rolling-over large debts became more difficult due to tighter lending standards. Interestingly, fluctuations in house prices at the city level are highly correlated with insolvency rates over the business cycle, suggesting that household balance sheets also play a role in the cyclical fluctuations of filings.

In chapter 4 we examine the large countercyclical fluctuations in U.S. bankruptcy filings and real credit card interest rates. In contrast to the prediction of standard consumption smoothing models, unsecured credit is pro-cyclical. To quantify the contribution of shocks to income and lending standards in accounting for the cyclical patterns in consumer credit markets, we introduce aggregate fluctuations into a heterogeneous agent life-cycle incomplete market model with a U.S. style bankruptcy regime. Aggregate fluctuations change the probability of persistent shocks to household earnings, with the likelihood of negative

income shocks increasing in recessions. We find that income fluctuations and endogenous borrowing constraints alone cannot generate cyclical debt to income and the volatility of filings and interest rates. Incorporating counter-cyclical intermediate shocks to the cost of lending helps the model match both volatilities, but not the debt pro-cyclicality.

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David Fieldhouse  
West Chester, Pennsylvania

March 27, 2014

*To Chantale*



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# **Co-Authorship**

The following thesis contains material co-authored by Igor Livshits and Jim MacGee. All authors are equally responsible for the work which appears in Chapters 3 and 4 of this thesis.

# Chapter 1

## Introduction

This work contributes to the areas of innovation and consumer credit. My dissertation consists of three chapters in macroeconomics. Chapter 2 examines the role of cross-sector complementarities in driving the observed patterns of innovation activity in the United States economy. Chapters 3 and 4 study consumer credit, and in particular, bankruptcy. These chapters are coauthored with Professors Igor Livshits and Jim MacGee. Chapter 3 is an empirical paper examining the drivers of bankruptcy filings using Canadian data. In chapter 4 a quantitative macroeconomic model explains consumers' decisions to declare bankruptcy and how this is impacted in a recession. The model is then calibrated to fit the observed patterns of bankruptcies in United States. Each chapter documents new empirical facts. Chapters 2 and 4 also provide new economic models to try to explain these new findings.

Innovation is often consider as the engine of economic growth. In Chapter

2, I show that the economy's production structure plays an important role in determining innovation. Using patent data, I document a set of empirical facts that are initially puzzling. I examine the relationship between the number and quality of patents at both the aggregate and industry level. I find a negative relationship at the aggregate level that, surprisingly, vanishes at the industry level. I reconcile the aggregate and industry relationships by considering interactions between industries. The average correlation between the number of patents in one industry and the quality of patents in another industry turns out to be negative. These interactions between industries make it difficult to interpret innovation data. A negative relationship between the number and quality of patents exists at the aggregate level and is widely seen to support the notion that patent counts largely reflect changes in rent-seeking behavior. However, focusing on the aggregate relationship between the number and quality of patents, ignores important inter-industry interactions. Specifically, the number and quality of patents are uncorrelated within industries. It is these inter-industry interactions, which drive the difference between the two relationships.

I propose that the inter-industry relationship results from the outputs of each industry being complements in the production of goods. When the quality of available ideas improves in one industry, the output of that industry will increase, which leads to increased demand in the complementary industry. This increases the returns from inventing in the second industry, and results in

their inventors developing ideas below the prior quality threshold. I develop a multi-industry innovation model to capture this mechanism. I also provide evidence that the inter-industry relationship strengthens with a measure of complementarities between any two industries.

Chapter 3 investigates the key factors that drive cyclical fluctuations in Canadian consumer insolvency filings, with a focus on the 2008-09 recession which witnessed an almost 50% above its pre-recession level. A natural explanation for the rise in insolvencies during recessions is an increased frequency of negative income shocks, manifested partly in the increased unemployment rate. Adverse income shocks place additional financial strain on debtors, which may make insolvency more likely. Another important mechanism comes from the supply side, as lenders may tighten their “lending standards” during recessions due to higher perceived risk of lending or higher internal cost of funds. More limited access to credit could make it harder for borrowers to roll-over existing loans or lead to higher interest rates for riskier borrowers, which could result in an increase in insolvencies.

We investigate the quantitative contribution of these two channels using aggregate data on insolvency filings, unemployment rates, debt levels, and key interest rates at the national, and city levels. Our empirical analysis finds support for both mechanisms, as both the unemployment rate and the financial market variables are statistically significant in explaining the variation in insolvency filings. The results are broadly consistent whether we consider

national level (annual or shorter quarterly series), or city level data. Interestingly, fluctuations in house prices at the city level seem to be related to fluctuations in the insolvency rates. Since home equity is the main asset of many households, changes in house prices could significantly impact the amount that households could borrow.

We use a unique dataset of insolvency filings in Canada that was provided by the Office Superintendent of Bankruptcy (OSB) to investigate how (and if) the characteristics of filers vary over the business cycle. These data also suggest that both adverse income and credit market conditions played a role in the rise in filings during the 2008-09 recession. We document that the fraction of unemployed among the filers does increase during the recession. A rough back-of-the-envelope analysis suggests that as much as a half of the rise in insolvencies may be due to increased unemployment. We also document an increase in the share of filers with “middle class” characteristics during the recession - a larger fraction of filers are homeowners, live with a spouse or a partner, have student loans, earn larger incomes, and are middle-aged. The average outstanding debts of filers are larger during the recession, supporting the hypothesis that rolling-over large debts became more difficult due either to tighter “lending standards” or to increased cost of funds.

These shifts in characteristics are broadly consistent with simple economic theory. As one would expect, unemployed filers became more prevalent during the recession. The increase in filers with “middle class” characteristics

suggests that the high levels of unemployment during the recent recession impacted households with stronger labour force attachment, who would during more usual economic times have a low probability of extended periods of unemployment. Simple economic theory suggests that the filers most affected by a tightening of “lending standards” are those with higher debt levels. This reflects both the fact that higher debt levels makes these households more vulnerable to higher interest rates (i.e., larger risk premia on loans to riskier borrowers) or to a tightening of credit lines which makes it more difficult to roll-over their debt. This mechanism also leads to more filers in a recession with “middle class” characteristics (such as higher levels of education and home ownership), since these characteristics are often a prerequisite for initial access to large amounts of credit.

In Chapter 4, I along with Professors Igor Livshits and Jim MacGee document that there are large countercyclical fluctuations in U.S. bankruptcy filings and real credit card interest rates, while unsecured credit is pro-cyclical. In this chapter, we document the facts and ask whether the predictions of incomplete market models with bankruptcy are consistent with these facts. We introduce aggregate fluctuations into a heterogeneous agent life-cycle incomplete market model with a U.S. style bankruptcy regime. Household borrowing is priced by competitive financial intermediaries who can observe households earnings, age and current asset holdings. Aggregate fluctuations change the probability of persistent shocks to household earnings, with the likelihood of negative shocks

increasing in recessions. This leads to asymmetric effects of credit pricing on different household types over the business cycles, since interest rates vary endogenously with borrowers default risk. The model is calibrated to match key features of the U.S. economy and bankruptcy system and cyclical movements in income.

We use the model to decompose the driving forces behind cyclical fluctuations in the consumer credit market and their impact on defaults. In particular, we seek to identify the impact of changes the composition of borrower risk on average interest rate and borrowing. The standard framework is found to miss the data in a couple dimensions. When the only source of aggregate uncertainty is income fluctuations, the calibrated model dramatically understates the volatility of bankruptcies and borrowing interest rates, and generates countercyclical borrowing. The increase in aggregate debt during recessions comes primarily from the extensive margin, as more households choose to borrow as a result of negative income shocks. The introduction of intermediation shocks during recessions reduces the gap between the model and the data, as we find that intermediation shocks can generate pro-cyclical borrowing and increase the volatility of both filings and interest rates. However, the benchmark model still significantly understates the volatility of bankruptcy filings.



## Chapter 2

# Innovation and Production Complementarities

### 2.1 Introduction

Innovation is widely considered the engine of economic growth.<sup>1</sup> In order to promote innovation, patent rights are awarded to those who invent. However, it is difficult to interpret changes in the number of granted patents. The trouble is that patent counts could reflect both the level of innovative output and the patent system at the time of application. As Figure 2.1 shows, U.S. patents have surged in number since the mid-1980s. Instead of attributing this surge to more innovation, many scholars and practitioners believe that changes to the patent system are responsible. For instance, Jaffe and Lerner [2004] contend that several bureaucratic changes unintentionally made patents both easier to secure and more beneficial to hold for rent-seeking purposes. The implication

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<sup>1</sup>Romer [1990] or Aghion and Howitt [1992] are two prominent examples of innovation's role in economic growth.

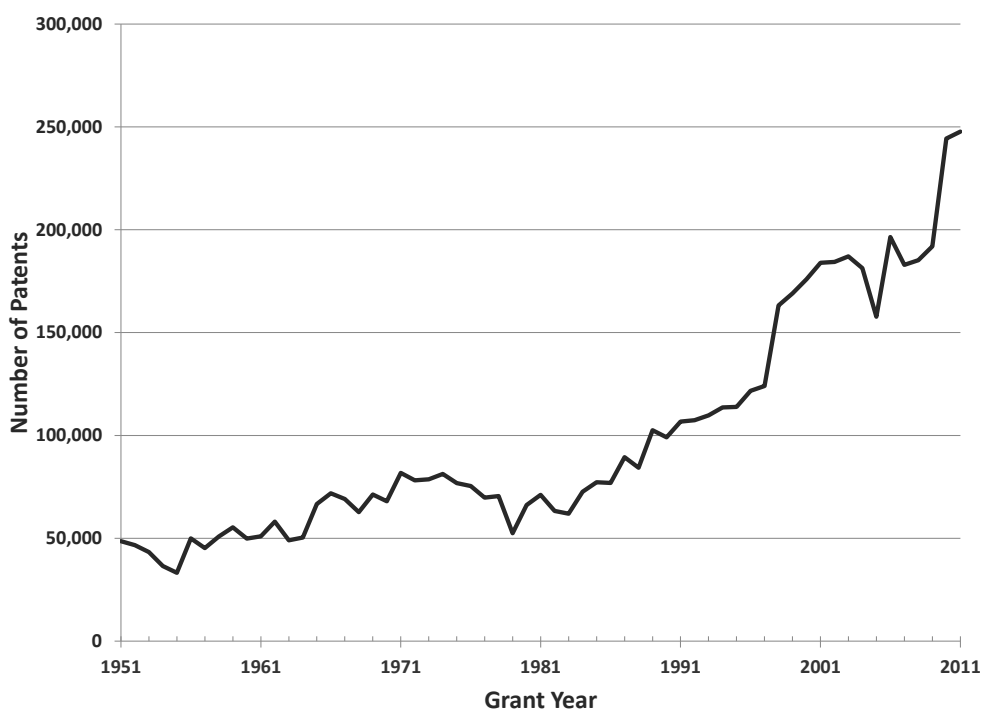
is that the “quality” of the marginal invention associated with a patent has declined. Consequently, this viewpoint suggests that over time the number of patents is negatively correlated with average patent quality (i.e. average associated invention quality). If there truly is such a correlation, there are profound implications for patent policy. Any social benefit from stronger incentives for invention must be weighed against the losses in consumer welfare which result from additional monopoly pricing [Nordhaus, 1969]. This negative correlation implies that there are diminishing benefits to awarding more patents. Furthermore, this correlation is consistent with the notion that patent counts rise from additional rent-seeking behavior. In particular, it is conventionally believed that the patents used to deter competitors are of particularly low-quality [Federal Trade Commission, 2003].<sup>2</sup> As a result – if the number and average quality of patents are negatively correlated over time – it is more likely that total welfare declines when the number of patents rises.

Using a standard proxy for patent quality, I compare the number and quality of patents over time, only to arrive at a puzzling set of observations. At the aggregate level, the number of patents is negatively correlated with average patent quality, which is consistent with patents being used to seek rents. However, I find that number and quality are uncorrelated within industries. The negative relationship between number and quality disappears as the classification of industries used in the comparisons becomes finer. By the 3-digit

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<sup>2</sup>More generally, patent protection is thought to discourage competition [Boldrin and Levine, 2008]. However, Aghion and Prantl. [2013] makes the case that this relationship may not be robust.

Figure 2.1: Annual U.S. Patent Grants



Source: U.S. Patent and Trademark Office

Standard Industry Classification, there is no statistically significant relationship between the number and average quality of patents. In contrast to the aggregate relationship, the industry-level evidence challenges the view that patent counts largely reflect changes in rent-seeking behavior.

More importantly, the relationship between patent number and quality differs when measured at the aggregate and industry level, because there are

significant and previously unrecognized interactions between industries. The correlation between patent number in one industry and average patent quality in another industry is typically negative. In fact, 91% of the aggregate relationship is due to this type of co-movement. To explain this inter-industry relationship, I propose that innovation decisions are related between industries due to the economy's production structure. In particular, I argue that innovation in one industry alters the returns from inventing in complementary industries. While it is well-established that innovative activities respond to changes in demand from other industries [Scherer, 1982], to the best of my knowledge, this is the first paper to consider how innovation decisions are linked between industries. I provide evidence for this novel relationship by relating the patent data to a measure of industry complementarities that I construct. I develop a simple multi-industry innovation model, which links industries through the production of a final good. I use the model to explain the puzzling observations in a unified framework. The model also provides testable implications, that allow me to identify the conditions which sign the aggregate relationship between the number and quality of patents.

The output of intermediate industries is related through production, as the production of final goods require goods from different industries. As a result, innovation is related. In particular, innovation in one industry alters the returns to inventing in another industry. To better understand how this mechanism explains the relationship between industries in the patent data, suppose

there are two industries with complementary output and fixed set of ideas that can be implemented (and thus patented). If one industry suddenly has higher quality ideas, more of them will be implemented and intermediate output increases for that industry, which results in more of the final good. Because of the complementarities, demand for the other intermediate good increases and this raises the returns for inventing in the industry where ideas are fixed. Ideas that were previously unprofitable due to their poor quality are implemented, implying there is a decline in average patent quality in the second industry.

I develop a model with two intermediate goods to capture the inter-industry relationship and use it to explain the puzzling observations. Innovation consists of implementing ideas, which implies that innovation and good production are a joint process. Joint production has been considered theoretically ([Shleifer, 1986]) and there is emerging empirical evidence for its prevalence ([Holmes and Kim, 2013]). Ideas vary in the quality of the intermediate good they can be used to produce. The intermediate goods are combined to produce a final good, which is in turn used for implementation. Use of the final good for innovation appears in lab-equipment models of economic growth and eliminates the role of knowledge spillovers ([Rivera-Batiz and Romer, 1991]).

I use the model to explore how innovation “supply” shocks in one industry affect innovation in the rest of the economy. The nature of these shocks is represented by changes in the quality-distribution of implementable ideas. If these supply shocks hit different industries throughout time, they can explain

the stylized facts. In the model, a shock produces a positive relationship between the number and average quality of implemented ideas in the originating industry. I explain the (lack of) correlation between number and quality at the industry level, by the internal shocks (producing a positive relationship) and external shocks (producing a negative relationship) averaging out over time. Finally, the aggregate relationship between the number and average quality of patents is negative, because it captures both the muted-within industry relationships along with the negative relationships between industries.

Complementarities between industries do not merely imply industries co-move together in terms of patent activities, they imply that the amount of co-movement between industries depends on the degree that any two industries are linked. As a result, co-movement between number and quality should be strongest when the industries are most complementary. Using input-output data, I construct a measure of complementarities between each industry pair. The idea of this measure is that industries are complementary if their outputs are used together in similar proportions. I find that as industry pairs become more complementary, the inter-industry patent relationship becomes more negative which supports the notion that complementarities explain the relationships between industries.

Besides providing a way to understand the relationships in the patent data, the model also offers a testable prediction. Without a model, it is unclear how

supply shocks produce a negative aggregate relationship between the number and average quality of patents. In particular, it is not always the case that the appearance of better ideas leads to a decline in the average quality of implemented ideas. The model provides the conditions that determine the correlation of the aggregate relationship between number and average quality of implemented ideas. I then use the model to show how innovation supply must have changed across industries for the aggregate relationship between the number and average quality of patents to be negative.

This paper is organized as follows. In Section 2.2, I review related literature. Section 2.3 documents the new empirical facts. In section 2.4, I develop the model and characterize the aggregate relationship between the number and quality of patents. In section 2.5, I provide evidence for asymmetric changes to innovation supply. These changes are consistent with those required to explain the empirical aggregate relationship between number and quality. In Section 2.6, I conclude and argue that these results question the conventional explanation of the patent surge.

## 2.2 Related Literature

### 2.2.1 Why Do Annual Patent Counts Change Overtime?

Several studies have directly linked patents to innovation.<sup>3</sup> However, patent counts may change for reasons unrelated to innovation. Schmookler [1954] argues that the ratio of patent applications to inventive activity depends on research complexity, scientific management, collaboration and a firm's ability to use inventions – all of which might change over time. Because of these concerns, Schmookler argues that it is more reliable to analyze fluctuations in patents instead of trends, as I do.

During periods where changes to the patent system are seen to be minor, patent counts are likely to be related to the level of inventive activity. During the 1970s research productivity appeared to be declining throughout the Western world. One explanation for the slowdown is exhaustion of inventive and technological opportunities [Griliches, 1990]. However, Schankerman and Pakes [1986] argue that research productivity actually increased during this time period. They construct estimates of European patent value using renewal information, and find that research productivity rose if you use value adjusted patents. Lanjouw and Schankerman [2004] reached a similar conclusion for U.S. patents by constructing an index of patent quality.

Hall and Ziedonis [2001] argued that a U.S. “patent paradox” began in the

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<sup>3</sup>See Igami [2013] for an example and summary.



mid-1980s. They note that patents surged while R&D grew modestly and the importance of patents declined in the eyes of R&D managers. They attribute the rise to changes in patent management. In contrast, Kortum and Lerner [1999] explain the rise by changes in R&D management. Both explanations are supported by patent activity rising across virtually all industries. I argue that patent counts can grow in multiple industries because certain industries are becoming more innovative and other industries respond through additional patenting.

### **2.2.2 Studies of Patent Quality**

The value of a patent is rarely observed. Several surveys exist however, and they suggest that patents are skew-distributed in their value. Scherer and Harhoff [2000] find that the top-deciles of eight different samples account for 48%-93% of the total respective sample value. In order to account for this heterogeneity systematically, one typically relies on more indirect measures of patent value. Similar to the much of the literature, I rely on forward citations – the number of future citations a patent receives. As far back as Trajtenberg [1990], citations have been used to indicate the importance of a patent. There is a well-established relationship between the number of citations a patent receives and its economic significance. Hall, Jaffe, and Trajtenberg [2005a],

Harhoff, Narin, Scherer, and Vopel [1999] and Bessen [2008] all show that citations are positively related to estimates or survey's of patent value. Furthermore, the citation-value relationship is supported by studies linking citations to variables which are thought to be correlated with patent value. These include whether the patent is litigated, the number of countries in which the patent is granted, and whether the patent is renewed.<sup>4</sup>

I find that there is negative relationship between the number and quality of patents over time. There is mixed evidence about the long-run correlation between the number and quality of patents in the literature. The estimates of patent value in Schankerman and Pakes [1986] and an index of patent quality in Lanjouw and Schankerman [2004] suggest the relationship is negative. Hall and Ziedonis [2001] compared the number and quality of patents in the semiconductor industry,<sup>5</sup> using citations. While they find no correlation between number and citations, they do not take this as evidence that quality of inventions associated with patents remained constant. They argue that applicants are including extra citations in order to withstand greater legal scrutiny.

One of the difficulties with understanding how patent quality changes over

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<sup>4</sup>See Bessen [2008] for a list of references.

<sup>5</sup>They focused on this industry due to it being one of the industries with the largest growth in patents.

time is that citations are difficult to compare over time. There have been several attempts to make citations comparable, but different methodologies produce different results about the trend in citations. Hall, Jaffe, and Trajtenberg [2001] and Mehta, Rysman, and Simcoe [2010] for example find opposite trends in average patent quality, because they differ in their approach to adjust citations. Hall, Jaffe, and Trajtenberg [2001] assumes a stationary age-distribution of citations, while Mehta, Rysman, and Simcoe [2010] allows it to vary over time. This second approach assumes that patent grant lags are exogenous - a controversial assumption by their own admission. Schmookler's concern about analyzing trends with patents is perhaps even more of a concern when citations are involved. Lanjouw and Schankerman [2004] argue that the 84% increase in patent citations from 1985 to 1993 can be explained by factors other than quality improvement, such as computerization which lowers the cost of citation. To avoid these issues, I compare annual differences in citations.

Although citations are the standard way to control for patent quality, one might seek an alternative measure. I do not use any alternative measures, because there are limitations to each. One alternative is to estimate patent value from renewal decisions,<sup>6</sup> but there are several issues regarding its use for U.S. data. First, any time series would be very short. Renewals are only available

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<sup>6</sup>Work such as Serrano [2010] uses patents transfers, but they are not publicly available.

for patents applied after 1983 and one must wait 14 years after a grant to observe their last renewal decision. Work by Bessen [2008] suggests that patent value grew after the mid-1980s, but it is unclear what implications this has on invention quality due to potential changes in the intellectual property regime. Furthermore, because nearly two-fifths of patents are fully renewed there is value truncation for the most valuable patents. One might use the number of countries for which the same invention is patented (patent family size) as a proxy for patent quality, but there are also concerns with truncation at the top of the value distribution, and Lanjouw and Schankerman [2004] contend that patent family size is much less important than citations. Beyond these two measures, backward citations, the number of claims, technical classes, the number of inventors are potential proxies for patent quality. However, these indicators are controversial [Nagaoka, Motohashi, and Goto, 2010].<sup>7</sup> Because many of these additional statistics are fairly controversial, I rely on the standard measure of quality: future citations from other patents.

### **2.2.3 Inter-Industry Relationships**

I document significant co-movement between industries in patent statistics.

Ouyang [2011] documents that most of aggregate R&D pro-cyclicality can be

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<sup>7</sup>Furthermore, they also produce mixed results when combined into composite indicators. Lanjouw and Schankerman [2004] found that patent quality increased since the mid-1980s, when using the number of claims, forward and backward citations, the family size, and technology area. The OCED (2008) uses a different composite indicator by incorporating the number of technical classes and inventors in their composite indicator. This index suggest that patent quality declined from 1990-2000 to 2000-2010.

accounted for by co-movement between industries. Co-movement is an important feature of the economy,<sup>8</sup> is explained by two potential forces: a single aggregate shock affecting all industries equally [Lucas, 1977], or by an industry-specific shock that propagates throughout the economy [Long and Plosser, 1983]. Specifically regarding innovation, there are some theories consistent with an aggregate explanation. Both Shleifer's (1986) theory of implementation cycles, and the more recent work by Francois and Lloyd-Ellis [2009] rely on aggregate demand externalities due to coordination. I rule out aggregate explanations, because they are inconsistent with the puzzling observations that are documented here. In particular, an aggregate explanation implies a similar relationship between the number and quality of patents at all levels of aggregation, which I do not find.

Similar to this paper, Chang [2013] finds that input-output relationships play an important role in the decision to innovate. He explains R&D co-movement as strategic interactions amongst supplying and purchasing industries.<sup>9</sup> I argue that independent actions produce a demand shock in another industry, which gives the appearance that innovation is coordination. Scherer [1982] reveals three-fourths of all U.S. industrial R&D is concerned with creating new or

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<sup>8</sup>The NBER's definition of a recession:

is a [persistent] period of decline in total output, income, employment, and trade, usually lasting from six months to a year, and marked by widespread contractions in many industries of the economy.

<sup>9</sup>R&D levels depend on the (annual) lagged values of another industry's R&D and whether the industry is a supplier of demander industry.

improved externally-sold products.<sup>10</sup> The model and explanation here broadly matches this feature, because most the intermediate good is sold to a final good industry.

### **Knowledge Spillovers**

I explain the new empirical facts by considering the role of demand externalities. However, other forces could produce the mechanism which explains the cross-industry relationship. One such mechanism is knowledge spillovers, which is well-established in other contexts [Griliches, 1998]. Both innovation and patenting allow for the transfer of knowledge, and some of this knowledge may spill into another industry without any market transaction taking place. In turn, this spillover could generate relationships across industries.

Qualitatively, knowledge spillovers are consistent with the stylized facts which I document. Consider two industries with independent demand for their products. Suppose the first industry develops a new invention, which results in more patents. If this lowers research costs, it leads to more patents in the second industry. If the second industry cites the first industry, it raises citations in the first industry and lowers the citation average in the second industry.<sup>11</sup> As a result, there is a negative correlation between the number of patents in one

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<sup>10</sup>He documents this by classifying patents according to their industry of origin and industry of use, and then creating a “technology flow” matrix which was used to assign the impact of R&D for a variety of industries.

<sup>11</sup>Citations are frequently used to track knowledge spillovers [Jaffe, Trajtenberg, and Henderson, 1993].

industry and quality in the other industry. As a result, the same theoretical inter-industry relationship could exist from knowledge spillovers.

There is evidence that knowledge spills across industries. Theoretically, knowledge transfer could occur in two ways. The Marshall-Arrow-Romer view contends that knowledge spillovers are more likely to occur between firms that share common knowledge. However, the Jacobs view contends that knowledge spillovers are strongest when combined with a distinct knowledge base. Bloom, Schankerman, and Van Reenen [2012] explores the possibility that knowledge spillovers occur across technology classes and evidence of spillovers across technologies. The empirical evidence on industries suggests that knowledge spillovers of the Jacobs type are the strongest. The studies using R&D as a proxy for innovation typically find that inter-industry knowledge spillovers are stronger than intra-industry knowledge spillovers.<sup>12</sup> Using patent citations as a proxy for knowledge spillovers, Fung and Chow [2002] look at global firms and find that on average 19.3% of the knowledge spillover is generated within the industries, with the rest stemming from other industries. However, Ngai and Samaniego [2011] argues their role may be small as the vast number of citations occur within industries.

However, knowledge spillovers will struggle to explain the timing of the empirical facts which I document. One key feature of knowledge spillovers is that

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<sup>12</sup>Autant-Bernard and LeSage [2011] find that Jacobs externalities are stronger than Marshall-Arrow-Romer in France. Bernstein [1988] find that inter-industry knowledge spillovers result in larger cost reductions than intra-industry knowledge spillovers in Canada.

they are highly localized at the time of patenting [Li, 2013]. Because knowledge takes time to diffuse at the national level, the impact from a particularly innovative industry may take several years to be realized. As a result, it is difficult to explain the contemporaneous relationship. Nevertheless, knowledge spillovers are an explanation which is complementary to the one told here.

## **2.3 New Facts**

Conventional wisdom largely suggests that there is a negative relationship between number and quality. In this section, I document the relationship between the number and quality of patents at different levels of aggregation. I use a standard measure of patent quality – citations from other patents – to compare the two. However, comparing citations over time is difficult for three reasons. There is citation truncation, along with changes to both the propensity to cite and future patent rates. Because there is no clear way to overcome all three factors, I analyze high-frequency data.

I find a puzzling set of new empirical observations. The average number of citations appears to be very elastic at the aggregate level. The average number of citations a patent receives declines by a third of the increase in patent number. This might suggest that changing patent standards are responsible for changing patent counts. However, I match patents to industries and examine the relationship within industries. As I compare the number and quality



at 1, 2 and 3-digit Standard Industry Classifications, the relationship between number and quality disappears as finer and finer classifications are used.

I reconcile the differences in the aggregate and industry-level relationships, by considering interactions between industries. I decompose the aggregate covariance between number and average citations into two components: a “within”-industry component reflecting how the number of patents and average quality co-vary within each industry, and a “between”-industry component capturing how number and average quality co-move between industries. I find that the latter accounts for 91% of the covariance. The aggregate relationship is negative, because the number of patents in one industry is negatively correlated with patent quality in another industry. That is, average patent quality declines when there is an increase in the number of patents in another industry.

In Section 2.4, I formally argue that production complementarities between industries account for the differences between the aggregate and industry level relationships. In this section, I provide empirical support for their role. Complementarities between industries not only imply there is co-movement between industries, they imply that the amount of co-movement between industries depends on the degree of linkage between any two industries. By constructing this complementarity measure, I am able to confirm the inter-industry relationship exists in the patent data. Using input-output data, I construct a measure of complementarities between industries, which is based

on the idea that industries are complements in production if their outputs are used in similar proportions throughout the economy. I provide empirical support for the explanation by constructing a measure of complementarities between each industry and relate this measure back to the patent data. Consistent with an explanation involving complementarities, I find that the inter-industry innovation relationship strengthens with the degree of complementarity between each industry pair.

I also consider an alternative explanation for the difference between the aggregate and industry-level relationships: compositional changes. I test whether industries with fewer citations are more volatile on average and this can account for the aggregate relationship. While I find some evidence that lower-“quality” industries are more volatile, the negative aggregate relationship still largely reflects interactions.

### **2.3.1 Measuring Patent Quality with Citations**

Each patent record contains a “References Cited” section. This includes any information relevant to a patent’s originality or “prior art.” Perhaps, the most important reference is that of another patent. A citation delimits the scope of the property rights awarded by the patent [Hall, Jaffe, and Trajtenberg, 2001]. It is the legal responsibility of the applicant to disclose any knowledge that contributed to their invention.<sup>13</sup> As a result, the number of citations that a

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<sup>13</sup>The examiner is also responsible to identify and include any omissions.

patent receives indicates technological significance. Citations are also linked to the economic significance of a patent.<sup>14</sup>

There are three reasons that raw citations are not directly incomparable over time. First, citations are naturally truncated. That is, younger patents have less opportunity to accumulate citations than older patents. Second, the propensity to cite has increased dramatically. Hall, Jaffe, and Trajtenberg [2001] documents that the average patent issued in 1999 makes over twice as many citations as the average patent issued in 1975.<sup>15</sup> Finally, the number of annual grants changes over time. This rise, along with the increasing citation propensity increases the total number of citations made. As a result, comparing citations from a “fixed-window” of time cannot be used to overcome the truncation.

To make citations comparable, they must be adjusted. To address the problem of truncated citations, one must estimate the shape of the citation-lag distribution.<sup>16</sup> There are two methodologies to estimate the shape of the citation-lag distribution. Hall, Jaffe, and Trajtenberg [2001] estimates the shape of the

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<sup>14</sup>Bessen [2008] summarizes several studies linking citations to a patent’s economic significance through variables thought to be correlated with patent value.

<sup>15</sup>They attributed this to differences in the U.S. Patent and Trademark Office (PTO) or technological areas, but Lanjouw and Schankerman [2004] suggest 84% of this rise is due to the use of computers to help pad patent applications with citations.

<sup>16</sup>Given this distribution, one can estimate the total citations of any patent by dividing the observed citations by the fraction of the population distribution that lies in the time interval for which citations are observed.

citation-lag distribution by assuming this distribution is stationary and independent of overall citation intensity. In contrast, Mehta, Rysman, and Simcoe [2010] estimates a citation-lag distribution which varies over time. To do so, requires variation in the time it takes for a patent to be granted. They assume that these lags are exogenous to the number of citations received. However, Popp, Juhl, and Johnson [2004] find that these lags are related to the number of citations received. The estimates provided by Hall, Jaffe, and Trajtenberg [2001] suggest that citations have risen over time. However, the estimates of Mehta, Rysman, and Simcoe [2010] suggest citations have declined.<sup>17</sup> These conflicting results highlight the difficulty in comparing citations. Instead, I compare the data at higher-frequencies where these methodologies produce qualitative relationship between number and quality.<sup>18</sup> I use a citation-adjustment factor which is based on the methodology from Hall, Jaffe, and Trajtenberg [2001], because it is more commonly used than the Mehta, Rysman, and Simcoe [2010] measure.

### **2.3.2 Methodology**

To examine the short-run relationship between number and average citations, I detrend the ln of each series with a Hodrick and Prescott [1997] filter. The filtering procedure decomposes each series into a sum of a cyclical component

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<sup>17</sup>Mehta, Rysman, and Simcoe [2010] claim that most of the differences are attributed to data rather than methodology, but this does not appear to be the case when comparing identical time periods.

<sup>18</sup>See Section 2.2.2 for a brief discussion.

and a stochastic trend that are uncorrelated from each other. By using ln data, one can interpret a deviation from trend as a percent difference. It is important to note that using growth rates instead of filtering the data produces quantitatively similar results – see Table 2.3.

To apply the filter, one must specify how it trades off the fit and smoothness of the trend. I set the smoothing parameter to 6.25 as argued to be appropriate for annual data by Ravn and Uhlig [2002]. Throughout the paper, I denote  $\hat{N}_t$  and  $\hat{Q}_t$  by

$\hat{N}_t =$  Deviations from trend of ln Patent Number during year  $t$ , and

$\hat{Q}_t =$  Deviations from trend of ln Average Adjusted Citations during year  $t$ .

The goal of the analysis is to provide stylized facts about the relationship between number and quality over time. To do so, I calculate correlation coefficients and elasticities between number and quality. The unit of analysis is the application year. Alternatively, one could use the grant year. The application year best reflects the expectation of the inventor, while the grant year best reflects change in the patent office. Because applications grow more rapidly than the grant rate, I analyze the data using the application date.

### 2.3.3 Sample

The primary data source is the 2010 revision of the National Bureau of Economic Research patent data. This dataset is publicly available as part of their

Patent Data Project or PDP.<sup>19</sup> The dataset contains the basic information in a patent record along with several additional statistics to analyze patents, which are documented in Hall, Jaffe, and Trajtenberg [2001]. The database consists of all utility patents.<sup>20</sup> All patents must be novel and non-obvious.

In the dataset, there are patents with application dates from 1963-2006. However, I only have reliable citation data from 1975-1995. Citations are only recorded on patents granted in 1976 or later. Because it takes 2 years on average for patents to be granted [Mehta, Rysman, and Simcoe, 2010], I drop patents with application dates before 1975. I analyze the series until 1995. While the data includes patents granted until 2006, many patents applied for in 2002 have yet to be entered in the dataset. In order to adjust the citations, a patent must have some time to accumulate citations. This is important because not allowing enough time for patents citation trends can take more than 5 years to appear [Sampat, Mowery, and Ziedonis, 2003].

In order to disaggregate the data, I match patents to firms which allows one to identify their industry. The vast majority of patents are assigned to corporations [Hall, Jaffe, and Trajtenberg, 2001]. About 47% of all patents are assigned to U.S. non-government organizations and 31% are assigned to non-U.S. non-government organizations. The remaining patents are either unassigned (18%) or belong to either individuals or governments (3%). In order to assign patents, I match patents to U.S. firms in Compustat – this is discussed

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<sup>19</sup>It can be found at <http://sites.google.com/site/patentdataproyect>.

<sup>20</sup>See Section A.5 for a discussion about the different types of patents.

in Section 2.3.4.<sup>21</sup>

I remove 5, 778 duplicate patent records that are the result of multiple-assignments. I drop 4 patents that are indicated to be missing or withdrawn. I further restrict the data set to firms in industries which account for the vast majority of R&D. This primarily consists of manufacturing industries in addition to a couple other industries. Scherer [1982] documents that agriculture, crude oil and gas production, air transport, communications, and the electric-gas-sanitary utilities sector argues are responsible for innovation.<sup>22</sup> The HP-filer cannot be applied to series with missing observations. To account for this, I further drop 21,495 patents or 136 three digit industries, because they fail to patent in a particular year.<sup>23</sup> In the end, I am left with 486,689 patents.

### **2.3.4 Matching Patents to Industries**

The PDP has undertaken extensive effort to provide a match between assignees and the securities in the North American Compustat dataset of firm financial information.<sup>24</sup> Bessen [2008] describes the matching procedure in great detail. Bessen [2008] finds that the matched firms account for 96% of the R&D

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<sup>21</sup>One can also analyze the data using technologies classes, which does not require any restrictions. This analysis produces a set of stylized facts.

<sup>22</sup>I do not include agriculture, because it is hard to interpret what it means for agriculture to be complementary.

<sup>23</sup>Surprisingly, this results in air transportation being omitted.

<sup>24</sup>In addition the matches identified in the 1999 NBER patent data, the PDP project has identified a number of additional matches using a name-matching program. This is important, because prior editions were based on the universe of firms in 1989.

performed by all U.S. Compustat firms.<sup>25</sup>

I obtained the firm data from the Wharton Research Data Services (accessed in July 2010). After matching the data to firms, I classify each patent by the assignee's standard industrial classification code. This classification refers to the firm's primary line of business as determined by Compustat. Unfortunately, the firm data only contains the current business-line, which implies industry classification can change over time. However, this issue is mitigated in two ways. First, the SIC was replaced by the NAICS in 1997. As a result, the SIC classification did not change after that date. Second, the matching procedure allows me to account for mergers and acquisitions. Whenever, there was a merger or acquisition I am able to use the industry classification that reflects the assignee's original business line.

Conceptually, there are two ways to think about patent classifications: origin or use.<sup>26</sup> The match that I use corresponds more with the industry of origin, because it is based on assignee name. Although it is possible to match patents to their industry of use,<sup>27</sup> the latter is rarely used because the end use of an innovation may correspond to several different industries.

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<sup>25</sup>They also account for 77% of all R&D-reporting firms listed in Compustat and 62% of all patents issued to domestic non-governmental manufacturing organizations between 1985 and 1991.

<sup>26</sup>See Hall and Trajtenberg [2004] for a discussion.

<sup>27</sup>See work by Silverman [2004].



Table 2.1: Industry Summary Statistics

	1 digit (n=4)		2 digit (n=22)		3 digit (n=87)	
	$N_i$	$Q_i$	$N_i$	$Q_i$	$N_i$	$Q_i$
Average	54077	16.4	14748	13.8	4818.7	13.2
Min	1349	9.4	136	5.7	136	5.6
Max	271322	27.5	88758	30.6	33823	32.5

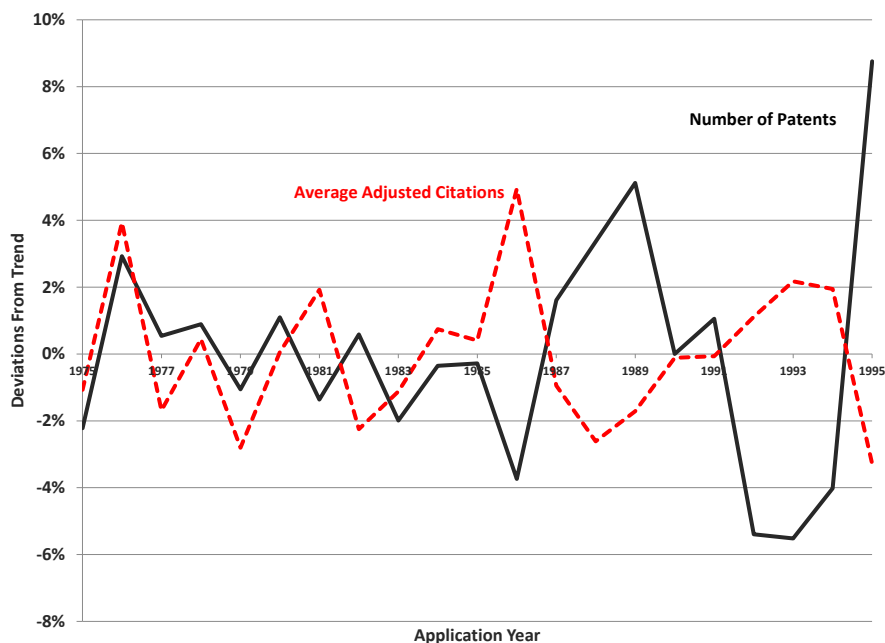
### 2.3.5 The Puzzle

The empirical analysis produces a puzzling set of observations: the number of patents is negatively correlated with average citations when measured at the aggregate level, but they are surprisingly uncorrelated when measured within industries. The aggregate relationship is consistent with patent counts reflecting changes in rent-seeking behavior. However, the industry-level relationship suggests that patent counts do not reflect changes in rent-seeking. In particular, any aggregate explanation for a rise in patents - say a change in the patent system - implies a negative correlation at both the aggregate and the industry level. Because the correlations differ, one must alternative explanations.

#### The Aggregate Relationship

Figure 2.2 plots the percent deviations in the number and the average adjusted citations of patents by application year. The two series are negatively

Figure 2.2: Deviations from Trend in the Number of Patents and their Average Adjusted Citations



correlated over time, with a correlation coefficient of  $-0.53$ .<sup>28</sup> The aggregate relationship is consistent with patent counts reflecting changes in rent-seeking behavior. That is, more low-quality patents are obtained as rent-seeking behavior increases. Because it is costly to develop high-quality inventions, these additional patents consist of inventions that are all of low-quality.

The two series suggest that there is moderate volatility in both the number and quality of patents. The standard deviation of number is 2.65%, which

<sup>28</sup>This correlation is similar when using the citations adjustments provided by Mehta, Rysman, and Simcoe [2010].

corresponds to annual change of about a thousand patents by U.S. firms and inventors. The standard deviation of a change in quality is 1.24%. The mean number of adjusted citations is about 15, which implies that the typical patent varies by a fifth of citation. Based on the estimates provided by Hall, Jaffe, and Trajtenberg [2005b], this would correspond to 0.6% change the average market value of a firm that patents.

### **The Industry-Level Relationships**

If aggregate patent counts are in fact changing because of an increase in rent-seeking behavior, patent counts within industries should reflect this as well. There is no reason, however, to suspect that all industries exhibit similar rent-seeking behavior. Hall [2007] provides two examples industry-specific changes in patenting practices. First, she argues that there has been a dilution of the application of the non-obviousness standard in biotechnology due to court decisions. She notes that the U.S. Patent and Trademark Office (PTO) now requires that new gene sequences to file a specific application or use to be granted. In the area of business methods, she notes that finding prior art on business method patent applications is problematic due to the absence of adequately written prior art documents. In response, the PTO now requires a second examination for these applications. Both examples highlight how there have been changes in the capacity of each industry to seek rents.

Table 2.2: Correlation between Quality and Number by Aggregation Level - Deviations from Trend

Aggregation Level	Agg.	1-digit	2-digit	3-digit
Industries (n)	1	4	22	87
Min		-0.58	-0.70	-0.79
Max		0.26	0.55	0.73
$\sum_{i=1}^n w_i \text{corr}(\hat{N}_i, \hat{Q}_i)$	-0.53	-0.35	-0.20	-0.11

### Correlations

For each industry, I detrend the logged series of patent number and average citations. Tables 2.2 and 2.3 summarizes these correlation coefficients for each level of disaggregation. I construct the weighted average for each industry based on their share of patenting over the entire sample. Denote by  $w_i$ , the fraction of patents filed over the period for industry  $i$ :

$$w_i = \frac{\text{Total Patents in Industry } i \text{ from 1975 to 1995}}{\text{Total Patents from 1975 to 1995}}.$$

Clearly, the weighted correlations coefficients are substantially smaller than the aggregate correlation. As a result, changes within any combination of industries, cannot account for the aggregate relationship. Furthermore, they decline as industry classifications become finer which suggests that incorporating interactions between industries might be responsible.

Table 2.3: Correlation between Quality and Number by Aggregation Level - Growth Rates

Aggregation Level	Agg.	1-digit	2-digit	3-digit
Industries (n)	1	4	22	87
Min		-0.61	-0.67	-0.81
Max		0.03	0.62	0.83
$\sum_{i=1}^n w_i \text{corr}(\hat{N}_i, \hat{Q}_i)$	-0.38	-0.26	-0.17	-0.10

Table 2.4: Regression Results: Elasticity between Number and Quality

	Agg	1-Digit	2-Digit	3-Digit
Coefficient	-0.337	-0.213	-0.018	-0.027
Standard Error	0.12	0.03	0.03	0.017
P-Value	0.011	0.01	0.008	0.105
95% Confidence Interval	[-0.59,-0.08]	[-0.37,-0.06]	[-0.09,0.05]	[-0.06,0.01]
$R^2$	0.2800	0.0816	0.0006	0.0014
$N$	21	84	462	1827

## Elasticities

The puzzle is also reflected in elasticities. I calculate the cyclical elasticity of patent number and patent quality by estimating the following statistical model

$$\hat{Q}_{i,t} = \beta \hat{N}_{i,t} + \epsilon_{i,t}. \quad (2.1)$$

at different levels of disaggregation. I omit the intercept, because each series has already been detrended and thus centered around zero. Once again, I weight the regression by each industry's long-run share of patents.

I report the elasticities in Table 2.4. At the aggregate level, the quality elasticity of patent number is statistically significant. A 1% increase in number

corresponds to a 0.38% drop in average quality. Once again, the relationship between number and quality disappears as finer classification of data are used. At the 3-digit level, a 1% increase in number corresponds to a change in quality which is indistinguishable from zero.

### 2.3.6 Decomposition

The aggregate relationship results from interactions between industries. Following Shea [2002] and Ouyang [2011], I approximate the change in the aggregate number of patents and average citations as the weighted averages of the  $N$  disaggregated industries. That is, I approximate number and quality as

$$\hat{N}_t \cong \sum_{i=1}^I w_i \hat{N}_i, \hat{Q}_t \cong \sum_{i=1}^I w_i \hat{Q}_i.$$

Let  $W$  be an  $1 \times N$  vector whose elements are  $w_i$ . Let  $\Omega^{NN}$ ,  $\Omega^{QQ}$  and  $\Omega^{NQ}$  be the  $N \times N$  variance-covariance matrices of number, quality, and between number and average citations. Then, the variance-covariance matrix of aggregate number and aggregate quality is approximately

$$\begin{pmatrix} Var(\hat{N}) & Cov(\hat{N}, \hat{Q}) \\ Cov(\hat{N}, \hat{Q}) & Var(\hat{Q}) \end{pmatrix} \cong \begin{pmatrix} W\Omega^{NN}W' & W\Omega^{NQ}W' \\ W\Omega^{NQ}W' & W\Omega^{QQ}W' \end{pmatrix}. \quad (2.2)$$

Each term in (2.2) can be further decomposed into a “within-industry” term from their diagonal elements, as the average variance (or covariance) of each industry’s own activities, and a “between-industry” term from the off-diagonal

elements, as the average co-movement between each industry’s activities with other industry’s activities.

Decomposing  $Cov(\hat{N}, \hat{Q})$  at the three-digit level reveals that the “between-” industry components account for 91% the aggregate covariance between the patent number and quality. This suggests there are strong interactions between industries. This type of interaction picks up the fact that the average correlation between the number of patents in one industry and the quality of patents in another industry is negative.

This degree of interaction between industries lines up well with Ouyang [2011], who looks at a related statistic. She argues that 94% of R&D procyclicality can be attributed to co-movement. One potential concern with this type of analysis is that the between-industry component will appear to be greater as the data becomes more disaggregated. This concern appears to be minimal, because even at the one-digit level it is 45% implying that there are interactions at a very coarse classification.

### **2.3.7 Complementarities**

Next, I present evidence that patent quality is negatively correlated with the number of patents in complementary industries. Based on Conley and Dupor [2003], I compute a measure of production complementarities between industries. The idea behind this metric is that any two industries complement each other if their outputs are used in similar proportions by other industries.

Using input-output data, I construct this measure and link it to the patent data. I indeed find that as industry pairs become more complementary, the inter-industry patent relationship becomes more negative. This is strong evidence that complementarities explain the number-quality patent relationship between industries.

### **The Use Table**

To capture how output flows between industries, I rely on one of the input-output tables in the U.S. economy. The table was published by Bureau of Economic Analysis (BEA). The table includes the consumption of various commodities by industries, final users as well as other non-producing industries. Because most commodities correspond to a specific industry, the use table captures the inter-industry flow of commodities. The table is published every five years. I use the 1987 version, which corresponds to the application year (1986).<sup>29</sup> The table is presented at the 95- and 480-industry detail, which corresponds to roughly the two- and six-digit 1987 SIC. One difficulty with the use table is that it includes suppliers and purchasers that do not correspond to any SIC capital-good industry. Suppliers include services and non-industries, such as wages and business taxes. Besides intermediate industries, purchasers also include their contribution to type of final use, ie. other components of GDP.

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<sup>29</sup>This table is described in detail by Lawson and Teske [1994].



Conley and Dupor [2003] focus on manufacturing industries, along with industries with significant R&D. I remove all final-use columns and drop all additional rows of the table except for employee compensation. Conley and Dupor [2003] limit the number of industries used out of concern that patterns may be obscured by the sheer amount of data.

### **A Measure of Industry-Complementarities**

The basic idea behind the complementary measure is that any two industries are complementary if their output are used in same proportions. The distance measure is calculated using the commodity flow from suppliers (the use table rows) to purchasers (the use-table columns).

To calculate the distance measure, it will be helpful to denote the input-output table by  $\Phi$ . The typical element  $\Phi(i, j)$  is the dollar value of compensation to industry  $i$  for goods used in industry  $j$ . With the modifications in Section 2.3.7 in place,  $\Phi$  is a  $27 \times 26$  nonnegative matrix. The columns of  $\Phi$ , correspond to the 25 two-digit SIC industries and one additional industry that sums all the industries that are low in R&D intensity. The rows of  $\Phi$  correspond to the compensation of the 26 industries above as well as to labor.

Conley and Dupor [2003] calculate the sell distance. I redefine their measure into a measure of complementarities. Specifically, I use a complementarities measure which is 1 less the sell distance.<sup>30</sup> That is,

$$\text{Comp}(i, j) = 1 - \left\{ \sum_{k=1}^N [\Psi(k, i) - \Psi(k, j)]^2 \right\}^{\frac{1}{2}}, \quad (2.3)$$

where

$$\Psi(i, j) = \frac{\Phi_t(i, j)}{\sum_{k=1}^N \Phi(k, j)}.$$

The second term in (2.3) is the sell distance, and represents how different the output usage is between any two industries. Because this measure is described in great detail in Conley and Dupor [2003], I omit a detailed analysis of it. Expression 2.3 is a measure of relative complementarities. That is, one cannot interpret a 0 measure of complementarities as a perfect substitutes.

## Results

I now compare how the relationship between number and quality over time ( $\text{corr}(N_i, Q_j)$ ) varies with the complementarity measure ( $\text{Comp}(i, j)$ ) developed above. There are several industries used to calculate the complementarity measure, which are not used in the sample. For this reason, I restrict the analysis to the industries listed in Table A.1. As Table A.1 shows the number of patents varies drastically between industries, so each observation will be weighted by  $w_i w_j$  where  $w_i$  is defined above.

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<sup>30</sup>There is no reason for the sell distance to be less than 1, but largest sell-distance is close to 1.

Figure 2.3: 2-Digit Cross-Industry Correlations between Number of Patents and Average Citations

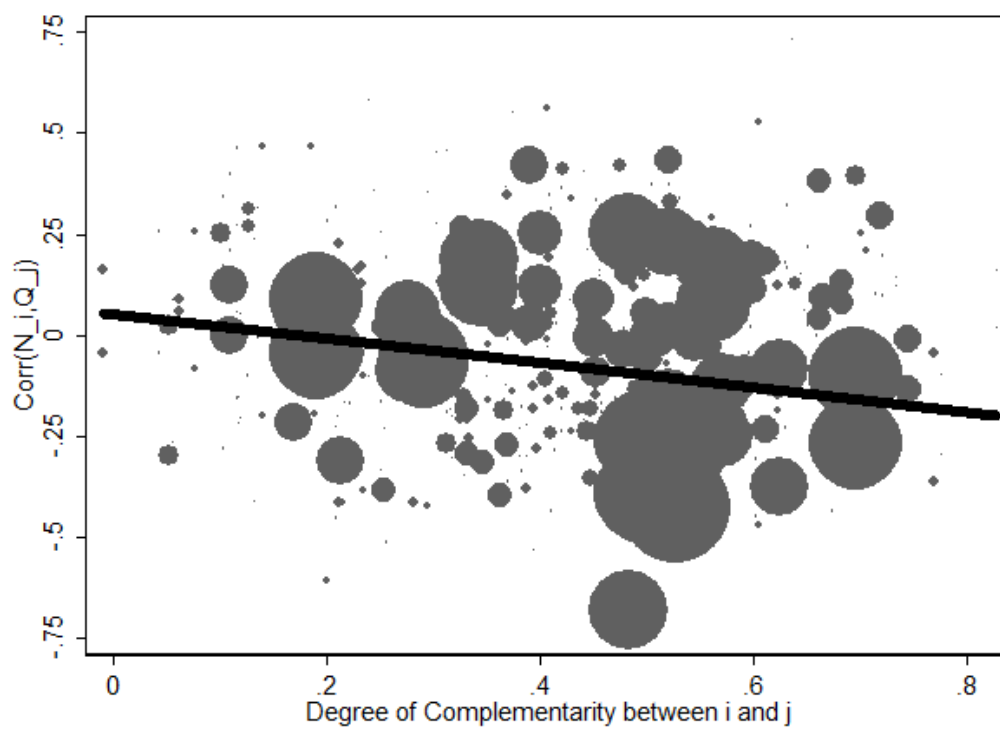


Table 2.5: Innovation and Complementarities

	Coef.	Std. Error	t	P>  t
Intercept	0.053	0.031	1.65	0.100
Comp(i,j)	-0.302	0.066	-4.55	0.000

Notes: The dependent variable is  $\text{corr}(\hat{N}_i, \hat{Q}_j)$ . Each observation is weighted by  $w_i \cdot w_j$ .  $N = 462$ ,  $R^2 = 0.431$ .

I test the following specification,

$$\text{corr}(\hat{N}_i, \hat{Q}_j) = \alpha + \beta \text{Comp}(i, j) + \epsilon_{i,j}. \quad (2.4)$$

The regression results are report in Table 2.5 and are plotted in Figure 2.3. There are two implications from this analysis. The results indicate that as industry pairs become more complementary, the inter-industry patent relationship becomes increasingly negative. This relationship supports the notion that complementarities explain the relationships between industries. In Section 2.4, I argue that innovation “supply” shocks in one industry affect innovation in the complementary industries. If these shocks change the distribution of implementable ideas, they result in more inventions in both industries, but the quality of the inventions decline in the complementary industry.

The second implication is that the relationships across industries are strongest in several industries of the economy. This reaffirms that an aggregate event cannot explain the relationships in the patent data. If that were the case, number and quality would be related regardless of the degree of complementarity between any two industries.

### 2.3.8 Alternative Empirical Explanation - Industry Composition

There is substantial variation in the number of citations that a typical industry receives. As Table 2.1 shows, the citation averages vary by as much as a factor of three. Because of this variation, I consider the role that compositional changes might play in explaining the stylized facts. Above, I document that number and citations are unrelated within industries. If interactions between industries were negligible, any change in average citations at aggregate level has to come from the composition of industries. If the cyclical increase in lowly-cited industries is larger, then the average number of citations that patents receive in aggregate will decline. As a result, this empirical explanation could account for the above observations.

In order to test this possibility, I compare the aggregate number of patents with their average citations when there are no compositional changes. If the aggregate correlation disappears when compositional changes are controlled for, then compositional changes are a possible explanation for the stylized facts.

To control for composition, I fix the weights (patent share) of each industry. Thus, I create an average quality series where the industry composition is constant:

$$\tilde{Q} = \sum_{i=1}^n w_i Q_i$$

and recompute the aggregate statistics with  $\tilde{Q}$  instead of  $Q$ .

At each disaggregation level,  $\text{Corr}(\hat{N}, \hat{Q})$  is similar to the original aggregate correlation coefficient. Using weights constructed at the 3-digit level,  $\text{Corr}(\hat{N}, \hat{Q}) = -0.29$ . Repeating the elasticity regressions, implies the quality elasticity of patent number is  $-.193$ . These results suggest that compositional changes can only account for about two-fifths of the aggregate relationship. In other words, compositional changes cannot solely explain the stylized facts.

In Section 2.5, I provide evidence that low-quality industries play a role in explaining the stylized facts. This explanation is consistent with the fact that compositional changes play some role in generating the stylized facts.

## 2.4 The Model

I develop a model that captures how innovation is related between industries. The model features two intermediate industries with homogeneous output. Innovation is broad in the sense that it consists of implementing ideas to produce an intermediate good. Each industry has an exogenous distribution of ideas that are varying in the quality of the intermediate good they produce. There are fixed costs to implementing an idea. As a result, only some of the ideas in each industry are implemented.

I use the model to explain the stylized facts by analyzing the impact of innovation supply shocks to one industry. In the model, a supply shock is represented by a shift in the distribution of implementable ideas. A positive supply

shock results in more ideas being implemented in each industry. In the originating industry, the average quality of implemented ideas increases. However, in the responding industry, there is a decline in average quality. This implies that there are both positive and negative relationships between the number and quality of implemented ideas at the industry-level.

The relationship between number and quality within an industry become muted, because the internal shocks (producing a positive relationship) and external shocks (producing a negative relationship) average out over time. The aggregate relationship between the number and average quality of patents captures both the muted-within industry relationships and the relationships between industries. Because there are both positive and negative relationships between-industries, the aggregate relationship is only negative when the inter-industry relationship are negative.

Without a model, one is unable to determine when the negative relationship between industries dominates the positive relationship. Intuitively, one expects that a positive supply shock would produce a positive-relationship between number and quality. However, I show that a negative aggregate relationship is indeed possible. A negative relationship occurs if the shock hits lower-“quality” industries. Conversely, if the shock occurs to the higher-“quality” the shock is positive. In Section 2.5, I find evidence for these types of shocks to explain the aggregate data.

### 2.4.1 Setup

The model is static. A representative consumer has linear preferences over the final good. The consumer is endowed with both the ideas that can be implemented in each industry and firms producing the final good. The economy's production structure is represented in Figure 2.4. The final good is produced by combining two intermediate goods. The final good has two uses. First, it is consumed. Second, it is required to implement an idea. The model is static, so the production occurs simultaneously.

The output of each industry is homogeneous.<sup>31</sup> Each industry is endowed with a set of ideas that vary in the quality of the intermediate good that they eventually produce. In this sense, an invention is synonymous with developing a different production method.

#### Production

The final good is produced by combining intermediate goods  $X_1$  and  $X_2$ . Specifically,

$$Y = (0.5X_1^{(1-\frac{1}{\epsilon})} + 0.5X_2^{(1-\frac{1}{\epsilon})})^{\frac{\epsilon}{\epsilon-1}}. \quad (2.5)$$

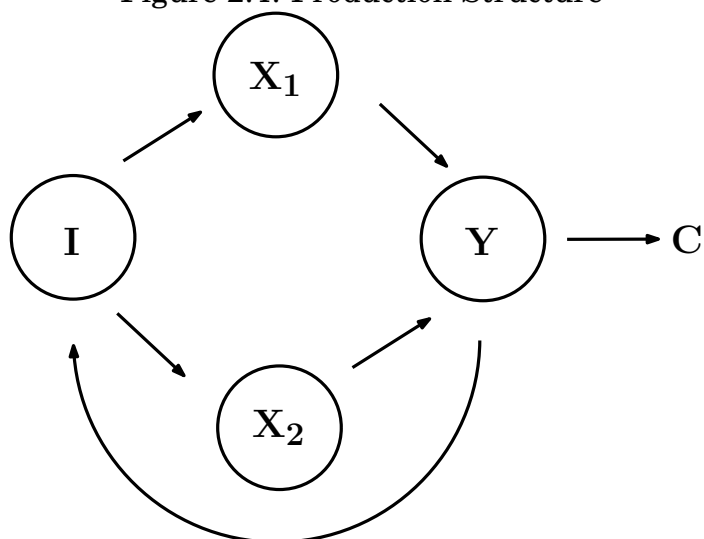
In this specification  $\epsilon \in (0, +\infty)$  represents the elasticity of substitution between industries. The degree of substitutability between the output of each industry increases in  $\epsilon$ . The special cases of  $\epsilon = 0$  or  $+\infty$  are left for Appendix

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<sup>31</sup>Omitting product innovation allows for a clearer demonstration about how the relative incentives to invest change between industries.



Figure 2.4: Production Structure



A.3. For expositional purposes, the effectiveness of each input is symmetric with respect to each input.<sup>32</sup>

In order to produce the intermediate good, ideas must be implemented. There is a pool of prospective inventors into each industry. Each inventor has an idea of known quality, but they must use a unit of the final good to implement it. Implementation produces a single unit of the intermediate good. Ideas vary in the quality of the intermediate good that they produce. That is, an idea of quality  $q_i$  produces  $q_i \cdot 1$  units of the intermediate good  $i$ . Then  $X_i$  is the combined output of the implemented ideas in each industry.

<sup>32</sup>The key result of this section (Proposition 4) is that the average quality of all implemented ideas is minimized when industries are identical in their innovation supply. When the share parameters differ, it is no longer the case that industries must be identical in their innovation supply. Nevertheless, average quality is still characterized by a U-shape.

## Ideas

The quality of ideas in each industry is distributed by a Pareto distribution with shape parameter  $k > 2$  over support  $[a_i, +\infty)$ .<sup>33</sup> Denote this distribution by  $G(a_i)$ . Under this distribution, the output of implementable ideas is skewed. The average quality of the underlying idea distribution is

$$\frac{ka_i}{k-1}.$$

A change in  $a_i$  can be thought of as supply shock, because it shifts the distribution of ideas in each industry. The supply shock is positive when  $a_i$  increases, because the quality of every implementable idea in industry  $i$  improves.

### 2.4.2 Equilibrium

The returns to implementing each idea decline in quality. As a result, there is a cutoff idea  $\phi_i^*$  where developing any lower-quality idea in industry  $i$  produces negative returns. The equilibrium is entirely described by the cutoffs  $\phi_1^*$  and  $\phi_2^*$ . To highlight how the incentives to implement are related between industries, I focus on a competitive equilibrium.

**Definition 1.** *A competitive equilibrium is a vector  $(\phi_1^*, \phi_2^*, N_1, N_2, X_1, X_2, R_1, R_2, Y)$  of idea cutoffs, measures of implemented ideas, measures of total intermediate outputs, intermediate good prices, and the total amount of final good produced such that the following conditions hold:*

---

<sup>33</sup> $k > 2$  ensures the first two moments exist.

- Given prices  $R_1$  and  $R_2$ , the final good producer solves

$$\max_{X_1, X_2} Y(X_1, X_2) - R_1 X_1 - R_2 X_2$$

- Given price  $R_i$  and idea of quality  $q$ , inventors implement the idea if

$$R_i q \geq 1$$

- The resource constraint is satisfied:  $Y(X_1, X_2) = C + N_1 + N_2$ .

- Aggregate Consistency

$$N_i = \int_{\phi_i^*}^{\infty} g_i(q) dq, \quad X_i = \int_{\phi_i^*}^{\infty} q g_i(q) dq$$

Given the distributional assumptions, in such an equilibrium, the number of implemented ideas in each industry is

$$N_i = \left( \frac{a_i}{\phi_i^*} \right)^k, \quad (2.6)$$

while the total output in each industry is

$$X_i = \frac{k a_i^k}{(k-1) \phi_i^{*k-1}}. \quad (2.7)$$

Dividing (2.7) by (2.6) gives the average quality for industry  $i$  :

$$Q_i = \frac{k \phi_i^*}{k-1}. \quad (2.8)$$

That is, the average quality of implemented ideas is proportional to the marginal idea that is implemented. The price of the intermediate good is inversely related to the quality of the marginal idea in that industry.

In Appendix A.1, I show that the cutoffs are given by

$$\phi_i^* = 2^{\frac{\epsilon}{\epsilon-1}} \left( \left( \frac{a_j}{a_i} \right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1 \right)^{\frac{1}{1-\epsilon}}. \quad (2.9)$$

It is important to note that the solution to the competitive equilibrium is also the solution to the planners problem. This would not be the case if there were knowledge spillovers.

### Aggregation

Denote by  $N$  the total number of ideas that are implemented:

$$N = N_1 + N_2.$$

Furthermore, I define the average quality of implemented ideas as

$$Q := \frac{N_1 Q_1 + N_2 Q_2}{N_1 + N_2}. \quad (2.10)$$

This definition assumes that inventions in different industries are comparable, which has to be implicitly assumed when one analyzes changes in the aggregate.

### 2.4.3 Correlated Shocks

From (2.9), the following proposition is apparent.

**Proposition 1.** *The average quality of implemented ideas is invariant to changes in innovation supply that are proportional in each industry.*

There are two effects from any shock. Suppose the supply shocks are positive. First, the increase in supply results in more of the intermediate good. As a result, the price of the intermediate good declines and the cutoffs should increase. However, because the intermediate goods are cheaper, more of the final good is produced. As the final good becomes more abundant, implementation costs decline equally for each industry and this should result in lower cutoffs. Because these two effects cancel each other out, the cutoffs do not change.

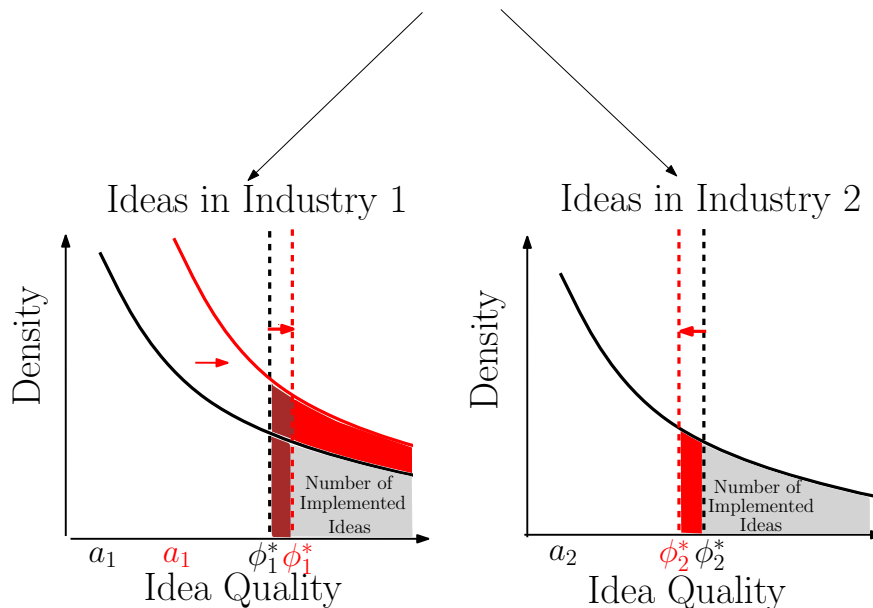
#### 2.4.4 Uncorrelated Shocks

I explore how a supply shock to one industry affects both industries. I begin by focusing on the “within” effect.

**Proposition 2** ( $\frac{\partial \phi_i^*}{\partial a_i} > 0$ ). *Better ideas in a industry imply that more ideas are produced, output increases and average quality increases within the industry.*

Figure 2.5 shows the impact of a positive supply shock hitting industry 1. As ideas become more productive in one industry, the output of each idea increases in that industry. The result is that the industry’s output becomes more abundant, which lowers the price of the good and raises the cutoff. It is less obvious how the number of implemented ideas changes, because there are two countervailing effects. First, increasing the cutoff results in fewer ideas being developed. However, there are now more ideas above the new threshold as well. Given the distributional assumptions, the net result is an increase in the number of implemented ideas.

Figure 2.5: Changes in Cutoffs from an increase in  $a_1$   
Final Good Producer



Now consider the impact of the shock on the other industry, which can be thought of as the “cross” effect.

**Proposition 3** ( $\frac{\partial \phi_i^*}{\partial a_j} < 0$ ). *Better ideas one industry imply that more ideas are produced, output increases and average quality declines in the other industry.*

As more of the final good is produced, the demand for the other intermediate good increases. Inventors respond by implementing more ideas, which can only be of lower quality.

**Corollary 1.** *Any supply shock results in the number of implemented ideas in one industry being negatively correlated with the average quality of ideas in the other industry.*

**Corollary 2.** *A positive supply shock increases the aggregate number of implemented ideas.*

Proposition 2 and 3 together imply that  $N$  rises when  $a_1$  increases.

**Corollary 3.** *Any supply shock result in the average quality of each industry moving in opposite directions.*

Proposition 2 and 3 imply that the cross-effect and within-effect are opposite in direction. As a result, the average quality of all implemented ideas depends on whether the cross-effect is greater than the within effect. In the next proposition, I show that average quality depends on the relative quality of ideas between industries.

### **Innovation Supply and Implemented Idea Quality: A U Relationship**

**Proposition 4** ( $\frac{\partial Q}{\partial a_i} < 0$ ,  $\frac{\partial Q}{\partial a_j} > 0$  if  $a_i < a_j$ ). *The average quality of the implemented ideas declines (increases) if ideas get better in the worse (better) industry.*

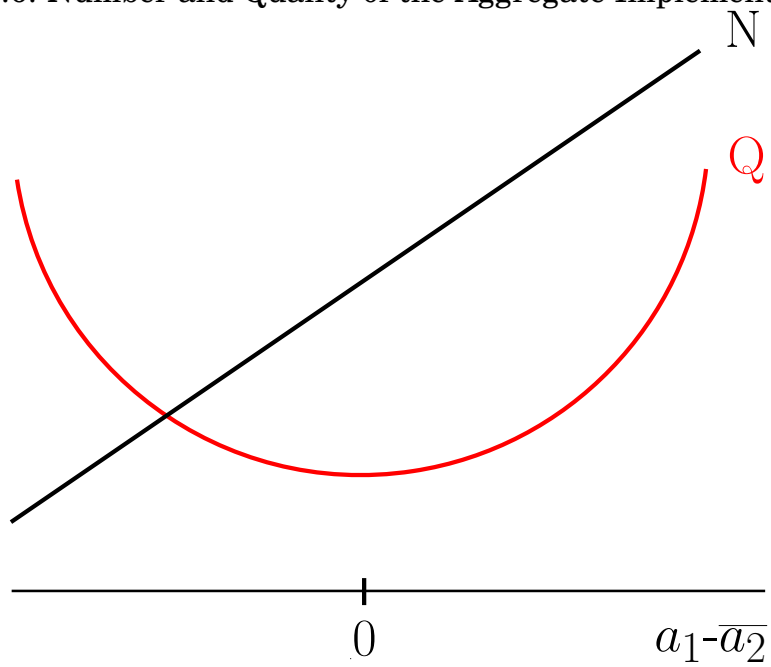
The proof can be found in Appendix A.2.

Figure 2.6 demonstrates how the average quality of implemented ideas changes when there is an increase in supply. To understand Proposition 4, consider the following example.

**Example 1.** *Final Good Production is Cobb-Douglas ( $\epsilon = 1$ ) with  $\theta = 0.5$*

**Fact 1.** *Aggregate quality is a weighted average of the average quality of each industry.*

Figure 2.6: Number and Quality of the Aggregate Implemented Ideas





**Proof.** The price is inversely related to the quality of the marginal idea in that industry. Using (2.6) and (2.7), the factor shares are proportional to the number of implemented ideas:

$$\frac{1}{\phi_i} X_i = \frac{k}{k-1} N_1 \quad (2.11)$$

With a Cobb-Douglas production, the expenditure share of each good is constant. The implication is that the average quality of all implemented ideas is determined by the cutoffs, because (2.10) reduces to

$$Q = \frac{Q_1 + Q_2}{2}.$$

Recall Corollary 3, which implies that any change in quality is always opposite in direction. For proposition 4 to hold, the following must be true.

**Fact 2.** *The cross-effect is smaller than the within-effect on quality when the shock occurs in the higher-quality industry.*

**Proof.** The expenditure share for each good is  $\frac{1}{2}$ . Using (2.11), it must be that

$$\frac{1}{2} = \frac{\frac{1}{\phi_1} X_1}{Y} = \frac{k N_1}{(k-1) N_1 \sqrt{Q_1 Q_2}} = \frac{k}{(k-1) \sqrt{Q_1 Q_2}}. \quad (2.12)$$

From (2.12) it obvious that any change to the average quality of ideas in one industry is opposite in direction but proportionally equal in magnitude. From (2.8) it must be that the cutoffs move in proportionally equal and opposite directions. As a result, the effect of a shock to any industry is always larger in level for the higher-quality industry. ■

To understand why the cross-effect is smaller when the shock occurs to a high-quality industry, suppose that  $a_1 < a_2$ . That is, industry 1 has relatively lower-quality ideas to implement. Recall, complementarities imply that  $N_1 = N_2$ . Prior to a shock, it then must be that industry 1 implements relatively lower-quality ideas compared to industry 2 ( $\phi_1 < \phi_2$ ). A positive shock to industry 2, lowers the cutoff in industry 1 to because it increases the price of good 1. However, it is very costly to produce more  $X_1$  ( $\frac{1}{\phi_1} > \frac{1}{\phi_2}$ ) because the cutoff only generates a small increase in output. As a result, the cross-effect is smaller when the shock occurs in the high-quality industry.

## 2.5 Evidence of Asymmetric Innovation Supply Shocks

In Section 2.4, I theoretically show that the relationship between the number and average quality of aggregate patents depends on the types of industries receiving an innovation supply (idea) shock. In particular, when a shock hits an industry which typically has ideas that are of relatively lower (higher)-quality compared to the other industries, the aggregate relationship will be negative (positive).

Over the entire sample time period, the number and average quality of aggregate patents is negatively correlated. However, as can be seen in Figure

2.2, the relationship is actually positive during the first-half of the time period. This variation in the aggregate relationship provides three testable predictions. In particular, to use the model to explain the time-series, requires that during the first sub-period, the supply of innovation in higher-quality industries is relatively more “volatile” compared to that of lower-quality industries; similarly, it must be relatively less “volatile” in both the second sub-period and the overall time series.

In this section, I identify innovation supply shocks and verify that they are consistent with these predictions. Using the patent data, I back out these shocks from changes in the number of highly-cited patents. The idea behind this approach is that the number of significant inventions indicates the quality of ideas that can be implemented. To test the predictions, I create two industries by aggregating the three digit industries according to their innovation supply. After doing so, I show that supply shocks to low and high-quality industries are asymmetric and consistent with the ones theoretically required to explain the data using the model.

### **2.5.1 Identifying Innovation Supply**

The decision to implement an idea depends on the demand for the good. This endogeneity of the decision to patent complicates the use of patents to identify the underlying distribution of ideas. To overcome this, I assume that the top of the supply distribution is related to the entire distribution of idea quality.

With this assumption, I can identify the supply of innovation by examining the most valuable patents. In particular, very valuable patents are always more valuable than the cost of patenting. As a result, the higher-quality ideas are patented immediately to ensure their monopoly rights are obtained.<sup>34</sup> Under this assumption, changes in the number of top patents identifies the distribution of ideas.

## 2.5.2 Ranking Industries by Quality

To test the model, I must compare the supply shocks low-quality industries to the ones in high-quality industries. This involves ranking and grouping industries together. Prior studies focus on R&D to Sales [Ngai and Samaniego, 2011, Klevorick, Levin, Nelson, and Winter, 1993], but this is controversial [Von Tunzelmann and Acha, 2005]. One difficulty with this measure is that R&D is an input into innovation. As a result, it is influenced by both demand and supply. Instead I rank industries according to 90th citation percentile. Due to the difficulty with citations changing over time, I make the comparison using the value in the median year - 1985.

To the best of my knowledge, this is the first paper to use citations to compare industries. This approach is supported in two ways. First, this measure of industry quality is positively correlated with R&D to sales for the firms that

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<sup>34</sup>While the US has a first-to-invent system, the first applicant to file for the patent still has the prima facie right to the grant.

were assigned patents.<sup>35</sup> Second, Hall and Trajtenberg [2004] documents that rapidly growing patent classes are associated with patent classes that receive more citations. These classes include information, data processing and multi-cellular biotechnology - all thought to be the most “innovative” technologies.

### 2.5.3 Supply Shocks

Next, I construct supply shocks for the “low” and “high”-quality industries. I group the ranked industries into two industries that are roughly equally-sized in terms of their long-run share of patents. I create two time-series that are the aggregation of the top ideas at three digit level. That is, I count the number of patents above the 90-th citation percentile trend in each industry  $-N_i^{90}$ . I then create two time series of the top ideas for the two aggregated industries:

$$\hat{N}_L^{90} = \sum_{\text{Low Quality}} N_i^{90} \text{ and } \hat{N}_H^{90} = \sum_{\text{High Quality}} N_i^{90}.$$

The supply shocks for the two representative industries are calculated as deviations in  $N_L^{90}$  and  $N_H^{90}$ .

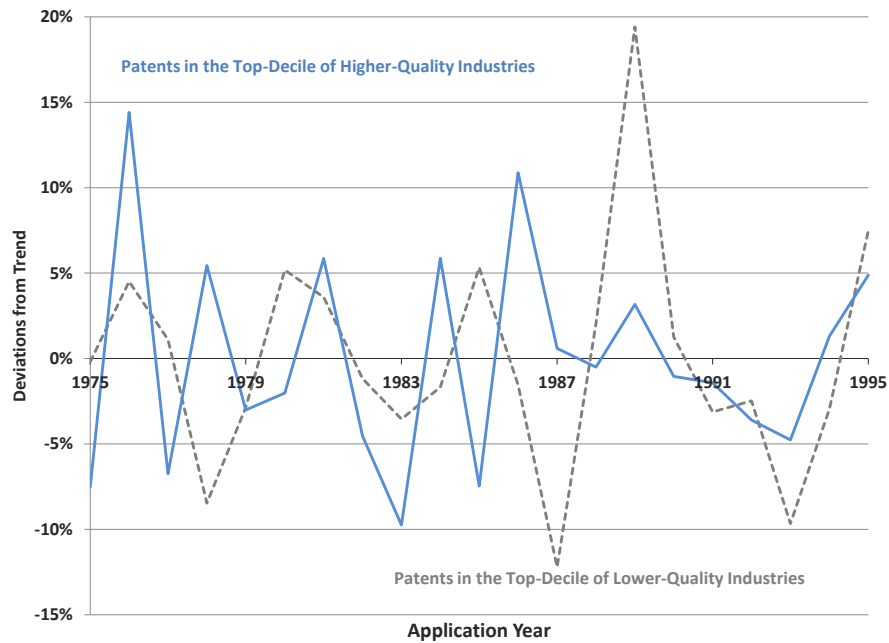
### 2.5.4 Results

Figure 2.7 plots the supply shocks for the “low” and “high”-quality industries. The figure does in fact suggest that the nature of the supply shocks between 1975-1984 were different from those in 1985-1995. In fact, Table 2.6 indicates

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<sup>35</sup>The correlation coefficient is 0.46.

Figure 2.7: Supply Shocks Aggregated by Industry Quality



that the negative aggregate relationship between number and quality is more prevalent during the second time period. I calculate the volatility for each sub-period and compare it with the aggregate relationship in Table 2.6. Indeed, the supply of innovation in higher-quality industries is relatively more “volatile” compared to that of lower-quality industries during the first sub-period, relatively less “volatile” in both the second sub-period and the overall time series.

Table 2.6: Supply Shocks and the Aggregate Relationship between the Number and Quality of Patents

	$\text{corr}(\hat{N}, \hat{Q})$	$\text{Std}(N_L^{90})/\text{Std}(N_H^{90})$
1975-1995	-0.53	1.07
1975-1984	0.48	0.56
1985-1995	-0.86	1.96

## 2.6 Conclusion

I argue that innovation decisions are related between industries with complementary output. When the output of two industries is complementary, innovation in one industry results in greater demand for the output of the other industry. As a result, the returns to innovation in the second industry increase and there is more innovation. If innovative output is heterogeneous in quality, the average quality of innovations in the second industry declines as lower-quality ideas are used in innovation. This mechanism explains a previously unconsidered relationship between industries in the patent data. Specifically, the number of patents in one industry is negatively correlated with the quality of patented inventions in another industry. I provide empirical support for the explanation by constructing a measure of complementarities between each industry and relate this measure back to the patent data. Consistent with an explanation involving complementarities, I find that the inter-industry innovation relationship strengthens with the degree of complementarity between each industry pair.

These interactions between industries make it difficult to interpret innovation data. A negative relationship between the number and quality of patents exists at the aggregate level and is widely seen to support the notion that patent counts largely reflect changes in rent-seeking behavior. However, focusing on the aggregate relationship between the number and quality of patents, ignores important inter-industry interactions. Specifically, the number and quality of patents are uncorrelated within industries. It is these inter-industry interactions from the production structure which drive the difference between the two relationships.

While I argue that patent statistics largely reflect innovation, patent quality declines when the number of patents increase. It is still an open question whether the responding industry is inventing or just seeking rents. Nevertheless, patents must in part be related innovation. Furthermore, these interactions make it difficult to attribute the entire surge in patents to changes in the patent system as an innovation supply shock to a particular industry can produce a decline in average patent quality due to the responses of complementary industries.



## 2.7 Bibliography

- AGHION, P., AND P. HOWITT (1992): “A Model of Growth through Creative Destruction,” *Econometrica*, 60(2), 323–51.
- AGHION, PHILIPPE, P. H., AND S. PRANTL. (2013): *Advances in Economics and Econometrics*.chap. Revisiting the Relationship between Competition, Patenting, and Innovation, pp. 451–455. Cambridge University Press, 1 edn.
- AUTANT-BERNARD, C., AND J. P. LESAGE (2011): “Quantifying Knowledge Spillovers Using Spatial Econometric Models,” *Journal of Regional Science*, 51(3), 471–496.
- BERNSTEIN, J. I. (1988): “Costs of production, intra-and interindustry R&D spillovers: Canadian evidence,” *Canadian Journal of Economics*, pp. 324–347.
- BESSEN, J. (2008): “The value of US patents by owner and patent characteristics,” *Research Policy*, 37(5), 932–945.
- BLOOM, N., M. SCHANKERMAN, AND J. VAN REENEN (2012): “Identifying technology spillovers and product market rivalry,” Discussion paper, National Bureau of Economic Research.
- BOLDRIN, M., AND D. K. LEVINE (2008): *Against intellectual monopoly*. Cambridge University Press Cambridge.
- CHANG, A. C. (2013): “Inter-Industry Strategic R&D and Supplier-Demander Relationships,” *Review of Economics and Statistics*, 95(2), 491–499.
- CONLEY, T., AND B. DUPOR (2003): “A Spatial Analysis of Sectoral Complementarity,” *Journal of Political Economy*, 111(2), 311–352.
- FEDERAL TRADE COMMISSION (2003): “To promote innovation: The proper balance of competition and patent law and policy,” Technical Report.
- FRANCOIS, P., AND H. LLOYD-ELLIS (2009): “Schumpeterian cycles with procyclical R&D,” *Review of Economic Dynamics*, 12(4), 567 – 591.

- FUNG, M. K., AND W. W. CHOW (2002): “Measuring the intensity of knowledge flow with patent statistics,” *Economics Letters*, 74(3), 353–358.
- GRILICHES, Z. (1990): “Patent Statistics as Economic Indicators: A Survey,” *Journal of Economic Literature*, 28(4), 1661–1707.
- (1998): “The Search for R&D Spillovers,” in *R&D and Productivity: The Econometric Evidence*, pp. 251–268. University of Chicago Press.
- HALL, B. H. (2007): “Patents and patent policy,” .
- HALL, B. H., A. B. JAFFE, AND M. TRAJTENBERG (2001): “The NBER patent citation data file: Lessons, insights and methodological tools,” *NBER working paper*.
- (2005a): “Market Value and Patent Citations,” *RAND Journal of Economics*, pp. 16–38.
- HALL, B. H., A. B. JAFFE, AND M. TRAJTENBERG (2005b): “Market Value and Patent Citations,” *The RAND Journal of Economics*, 36(1), pp. 16–38.
- HALL, B. H., AND M. TRAJTENBERG (2004): “Uncovering GPTS with Patent Data,” NBER Working Papers 10901, National Bureau of Economic Research, Inc.
- HALL, B. H., AND R. H. ZIEDONIS (2001): “The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995,” *RAND Journal of Economics*, 32(1), 101–28.
- HARHOFF, D., F. NARIN, F. M. SCHERER, AND K. VOPEL (1999): “Citation Frequency And The Value Of Patented Inventions,” *The Review of Economics and Statistics*, 81(3), 511–515.
- HODRICK, R. J., AND E. C. PRESCOTT (1997): “Postwar U.S. Business Cycles: An Empirical Investigation,” *Journal of Money, Credit and Banking*, 29(1), 1–16.
- HOLMES, T. J., AND B. KIM (2013): “Measuring the Joint Production of Goods and Ideas,” .
- IGAMI, M. (2013): “Patent Statistics as Innovation Indicators? Hard Evidence,” *Hard Evidence (May 10, 2013)*.

- JAFFE, A. B., AND J. LERNER (2004): *Innovation and its discontents: How our broken patent system is endangering innovation and progress, and what to do about it*. Princeton Univ Pr.
- JAFFE, A. B., M. TRAJTENBERG, AND R. HENDERSON (1993): “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations,” *The Quarterly Journal of Economics*, 108(3), 577–598.
- KLEVORICK, A. K., R. C. LEVIN, R. R. NELSON, AND S. G. WINTER (1993): “On the Sources and Significance of Interindustry Differences in Technological Opportunities,” Cowles Foundation Discussion Papers 1052, Cowles Foundation for Research in Economics, Yale University.
- KORTUM, S., AND J. LERNER (1999): “What is behind the recent surge in patenting?,” *Research Policy*, 28(1), 1–22.
- LANJOUW, J., AND M. SCHANKERMAN (2004): “Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators,” *The Economic Journal*, 114(495), 441–465.
- LAWSON, A. M., AND D. A. TESKE (1994): “Benchmark Input-Output Accounts for the U.S. Economy, 1987.,” *Survey Current Bus.*, 74, 73–115.
- LI, Y. A. (2013): “Borders and Distance in Knowledge Spillovers: Dying Over Time or Dying with Age? - Evidence from Patent Citations,” MPRA Paper 53528, University Library of Munich, Germany.
- LONG, J. B. J., AND C. I. PLOSSER (1983): “Real Business Cycles,” *Journal of Political Economy*, 91(1), 39–69.
- LUCAS, R. E. (1977): “Understanding business cycles,” *Carnegie-Rochester Conference Series on Public Policy*, 5(1), 7–29.
- MEHTA, A., M. RYSMAN, AND T. SIMCOE (2010): “Identifying the age profile of patent citations: new estimates of knowledge diffusion,” *Journal of Applied Econometrics*, 25(7), 1179–1204.
- NAGAOKA, S., K. MOTOHASHI, AND A. GOTO (2010): “Chapter 25 - Patent Statistics as an Innovation Indicator,” in *Handbook of the Economics of Innovation, Volume 2*, ed. by B. H. Hall, and N. Rosenberg, vol. 2 of *Handbook of the Economics of Innovation*, pp. 1083 – 1127. North-Holland.
- NGAI, L., AND R. SAMANIEGO (2011): “Accounting for research and productivity growth across industries,” *Review of economic dynamics*, 14(3), 475–495.

- NORDHAUS, W. D. (1969): "An economic theory of technological change," *The American Economic Review*, 59(2), 18–28.
- OUYANG, M. (2011): "Pro-cyclical Aggregate R&D: A Comovement Phenomenon," *Working Paper*.
- POPP, D., T. JUHL, AND D. JOHNSON (2004): "Time In Purgatory: Examining the Grant Lag for US Patent applications," *Topics in Economic Analysis & Policy*, 4(1).
- RAVN, M. O., AND H. UHLIG (2002): "On adjusting the Hodrick-Prescott filter for the frequency of observations," *The Review of Economics and Statistics*, 84(2), 371–375.
- RIVERA-BATIZ, L. A., AND P. M. ROMER (1991): "Economic integration and endogenous growth," *The Quarterly Journal of Economics*, 106(2), 531–555.
- ROMER, P. M. (1990): "Endogenous Technological Change," *Journal of Political Economy*, 98(5), S71–102.
- SAMPAT, B., D. MOWERY, AND A. ZIEDONIS (2003): "Changes in university patent quality after the Bayh-Dole act: a re-examination," *International Journal of Industrial Organization*, 21(9), 1371–1390.
- SCHANKERMAN, M., AND A. PAKES (1986): "Estimates of the Value of Patent Rights in European Countries during the Post-1950 Period," *Economic Journal*, 96(384), 1052–76.
- SCHERER, F. M. (1982): "Inter-Industry Technology Flows and Productivity Growth," *The Review of Economics and Statistics*, 64(4), 627–34.
- SCHERER, F. M., AND D. HARHOFF (2000): "Technology policy for a world of skew-distributed outcomes," *Research Policy*, 29(4-5), 559–566.
- SCHMOOKLER, J. (1954): "The Level of Inventive Activity," *The Review of Economics and Statistics*, 36(2), 183–190.
- SERRANO, C. (2010): "The dynamics of the transfer and renewal of patents," *RAND Journal of Economics*, 41(4), 686–708.
- SHEA, J. S. (2002): "Complementarities and Comovements," *Journal of Money, Credit and Banking*, 34(2), 412–33.
- SHLEIFER, A. (1986): "Implementation cycles," *The Journal of Political Economy*, pp. 1163–1190.

- SILVERMAN, B. S. (2004): “Documentation for International Patent Classification - U.S. SIC concordance,” [http://www-2.rotman.utoronto.ca/~silverman/ipcsic/documentation\\_IPC-SIC\\_concordance.htm](http://www-2.rotman.utoronto.ca/~silverman/ipcsic/documentation_IPC-SIC_concordance.htm), Accessed: 2012-06-30.
- TRAJTENBERG, M. (1990): “A Penny for Your Quotes: Patent Citations and the Value of Innovations,” *RAND Journal of Economics*, 21(1), 172–187.
- VON TUNZELMANN, N., AND V. ACHA (2005): “Innovation in low-tech industries,” *The Oxford handbook of innovation*, pp. 407–432.

## Chapter 3

# Income Loss and Bankruptcies over the Business Cycle

### 3.1 Introduction

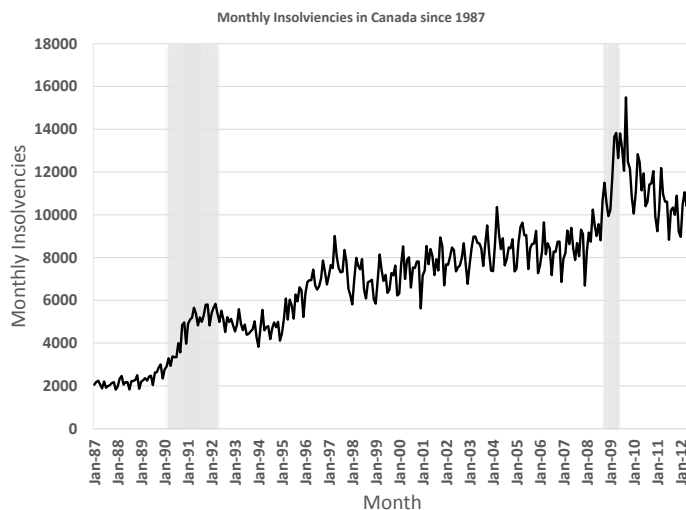
The 2008-2009 recession witnessed a sharp and rapid jump in Canadian consumer bankruptcies and proposals (see Figure 3.1). The insolvency rate peaked at nearly 50% above its pre-recession level.<sup>1</sup> While the rise in insolvency during a recession is not surprising, there is surprisingly little agreement over what factors account for these cyclical fluctuations. This reflects an ongoing debate about the relative importance of “economic shocks” and poor financial management in accounting for personal bankruptcies.

To assess the underlying drivers of cyclical fluctuations in filings, we examine both micro and macro data. Our micro level analysis makes use of a unique data set containing demographic characteristics (age, gender, family size) as

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<sup>1</sup>The consumer insolvency rate is the number of consumer bankruptcies and proposal per thousand adults.

Figure 3.1: Monthly Consumer Insolvencies (Bankruptcies and Proposals) in Canada since 1987



well as the nature of debts, assets and income of Canadian insolvency filers from January 1, 2005 to June 30, 2011.<sup>2</sup> We use this data to examine the contribution of unemployment to the rise in filings during the recession, as well as to document cyclical changes in the characteristics of insolvency filers. Given the short period covered by this data, we also examine aggregate data at the national, and city level to examine the contribution of unemployment rates, debt levels and interest rates to cyclical fluctuations in personal insolvency filings since the 1980s.

We use this data to quantify the contribution of two channels that may drive

<sup>2</sup>The data was provided by the Office of the Superintendent of Bankruptcy (OSB), and is from mandatory forms completed by filers.

cyclical movements in insolvency filings and consumer credit. First, increased income volatility (reflected in higher unemployment rates) during recessions could financially strain some households, potentially triggering greater demand for loans and higher insolvencies. The other channel, which we refer to as changes in “lending standards,” focuses on how borrowers respond to changes in their access to credit. Of course, it is possible that lending standards tighten in response to increased default risk from a rise in job losses. This theoretical relationship is explored in Chapter 4.

Our focus on these channels is motivated by the literature and aggregate data. As Figures 3.2 and 3.3 illustrate, the rise in insolvencies closely tracked the rise and decline in the unemployment rate.<sup>3</sup> This positive correlation between personal insolvency filings and unemployment rates is consistent with the patterns observed during the recessions of the early 1980s and 1990s (see OSB, 2007).<sup>4</sup> While the correlation between unemployment rates and insolvency filings suggests that declining income help account for cyclical movements in filings, their quantitative contribution remains debated.

Credit market changes may also impact borrower incentives to file for bankruptcy. A tightening of lending standards during recessions may make filing more attractive for heavily indebted borrowers faced with lenders unwilling to rollover existing debt or higher interest rates. Changes to (internal) cost of funds of

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<sup>3</sup>Figure 3.3 excludes filers who ran a business in the last 5 years and those with liabilities larger than \$1,000,000.

<sup>4</sup>Similar patterns for the U.S. are documented in Chapter 4.



Figure 3.2: Annual Unemployment and Consumer Insolvency Rate: 1966-2011

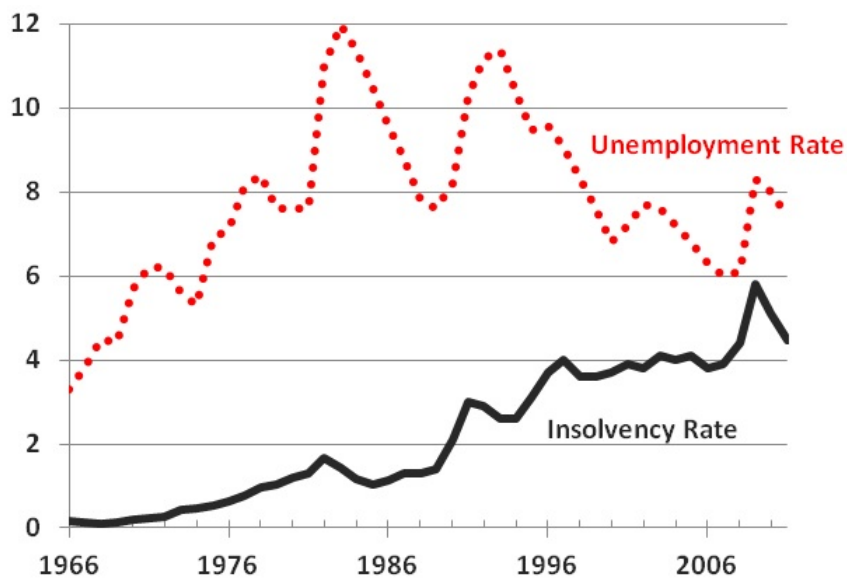
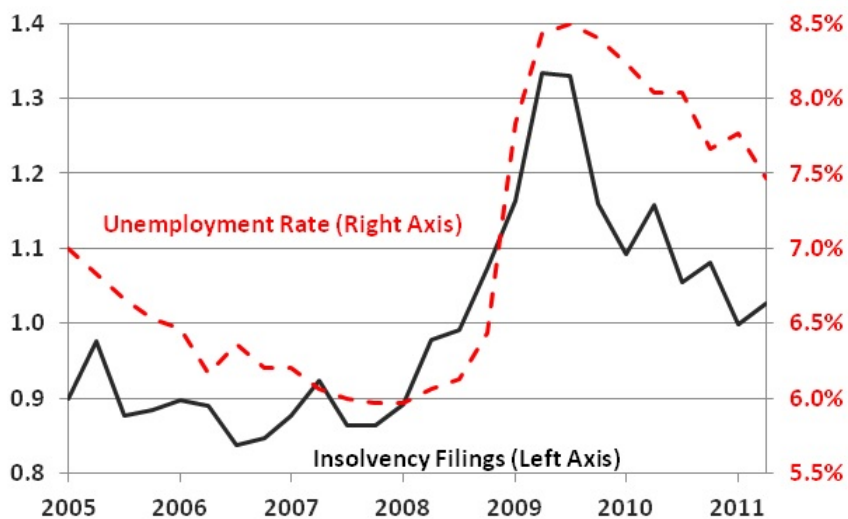


Figure 3.3: Quarterly Unemp. and Consumer Insolvency Rate: 05Q1-11Q2



lenders may lead to similar outcomes, by either increasing the cost of loans or inducing lenders to restrict access to credit.<sup>5</sup> Indeed, credit bureau data suggests that “marginal” borrowers had the greatest loss in credit access (deRitis, Ackcay, and Kernytsky [2012]).

Our findings suggest both of these channels play an important role in cyclical movements in insolvencies. Our regression analysis at the national level indicates that cyclical fluctuations in unemployment rates and consumer interest rates play the largest role in accounting for business cycle movements in insolvency rates. We find similar results using cross-city variation in unemployment and insolvency rates. We also analyze 11 Canadian cities for which we have house price data from 1999 to 2012. In this case, we find that unemployment and house price changes play an important role in accounting for variation in filings across cities.

The filer level data also suggests that unemployment and credit market conditions are significant factors in accounting for cyclical fluctuations in filings. As a rough measure of the contribution of unemployment, we compute the fraction of the increase in insolvency filings (relative to 2007) due to filers who report either no employment income or employment insurance income when filing (see Table 3.15). This suggests that 40 to 60 percent of the rise in filings over 2008 – 2011 may be directly attributable to labour market shocks.<sup>6</sup> Our

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<sup>5</sup>Chapter 4 builds a formal analytical structure with the objective of using quantitative economic theory to derive empirical predictions.

<sup>6</sup>It is difficult to say if this is an upper or lower bound. On the one hand, some filers could have experienced job loss prior to filing that contributed to higher debt levels. Conversely, some

findings suggest that credit market conditions may help account for the rise in filings. While the recent recession saw a fall in short term borrowing rates, both the credit bureau (which indicate a tightening of lending standards) and the fall in house price suggest that some households may have found access to credit more difficult. This is consistent with the significant contribution of home owners (which we identify as filers reporting having mortgage debt) to the rise in filings.

The rise in filings was largely driven by more “*middle-class*” filers. We document this in several ways. First, we observe that the fraction of filers receiving unemployment benefits rises, which suggests individuals with stronger ties to the labour market (given the requirements to qualify for unemployment benefits) are contributing to the rise. We also see a growth in the average monthly income, assets and debts during the recession. In addition, a larger fraction of filers were middle-aged, owned their home, and cohabited with a partner.<sup>7</sup> Both the mix of debt (increased share of housing debt and higher debt levels) suggest that many filers would have had pre-recession income levels to support this debt. To the extent that the average assets (and liabilities) of filers is a good proxy for the cyclical rise in “*middle-class*” filers, the 2008-09 recession appears to be broadly consistent with patterns observed in past recessions (see Figures 3.4 and 3.5).

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people with no income could have been pushed into filing due to tighter lending standards, with the issue of employment income playing a secondary role.

<sup>7</sup> We compare the filer population to the general population (using Statistics Canada data), and find that these changes are not driven by shifts in the characteristics of the Canadian populace.

Figure 3.4: Average Bankruptcy Filer Assets in 2002 Dollars: 1976-2009

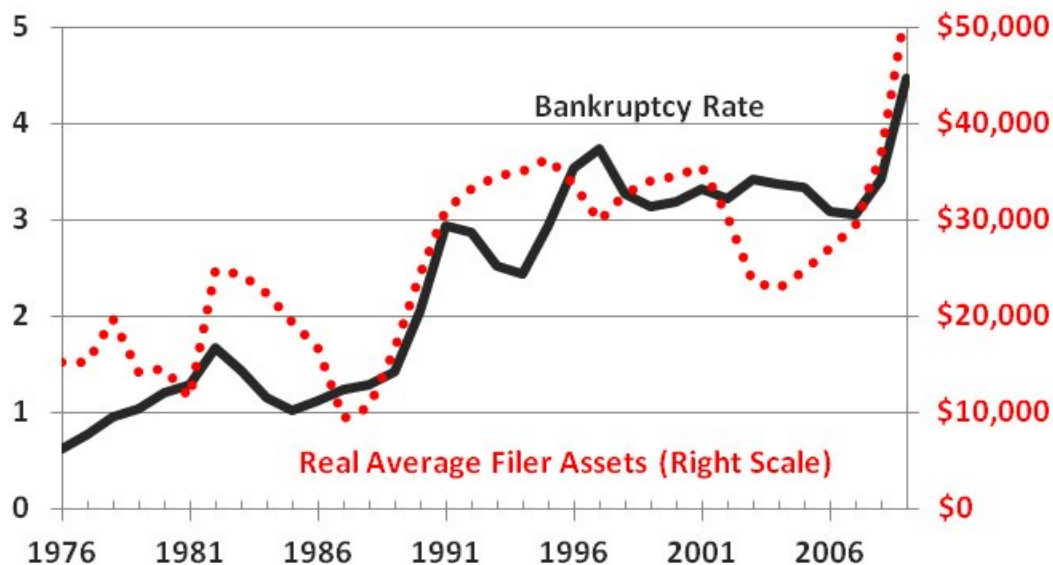
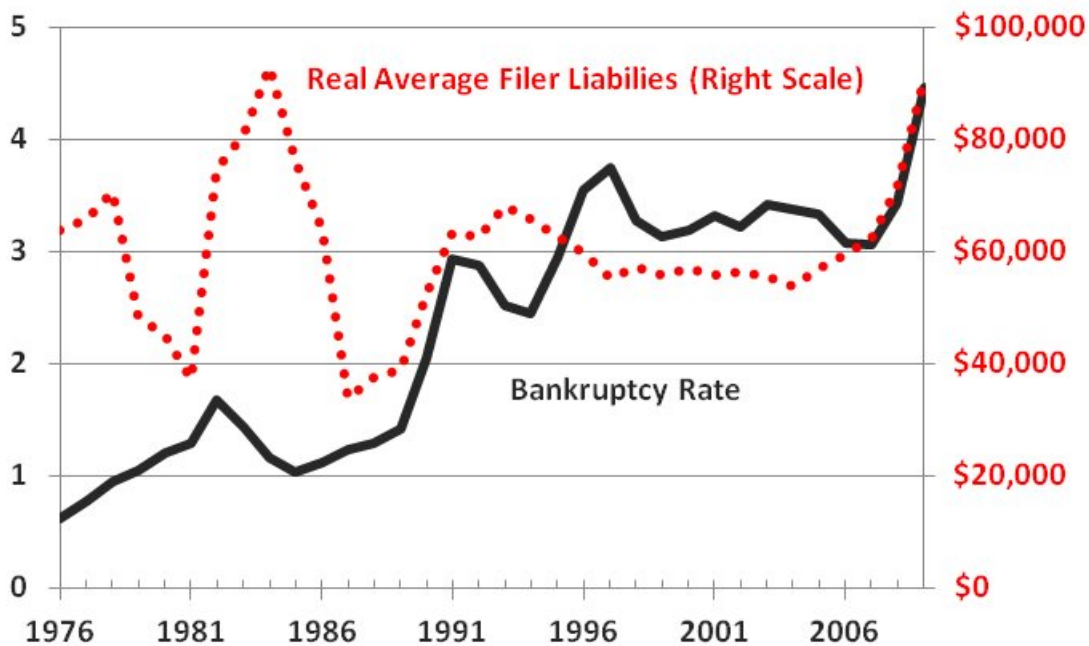


Figure 3.5: Average Bankruptcy Filer in 2002 Dollars: 1976-2009



Our findings offer insight into the debate over whether bankruptcies are driven by adverse shocks or “strategic” debtors. One view, exemplified by the findings of Sullivan, Warren, and Westbrook [2000], is that (negative) income shocks are a key factor in many (up to two-thirds) of U.S. bankruptcies. In contrast, Fay, Hurst, and White [2002] conclude that adverse income shocks do not play a significant role in accounting for filings. Our analysis lends support to both views. Using the Survey of Financial Security, we use filer demographic characteristics and balance sheets to impute their income. While we find that imputed and actual income for non-homeowners are relatively similar, for filers with mortgage debt our imputed income measure is much larger than the reported income. As we find that homeowners can account for a large fraction of the rise in filings during the last recession. We interpret this as suggesting that economic shocks are a key factor in cyclical movements in filings. However, our findings are consistent with many filers (particularly during “normal” economic times) experiencing relatively small income shocks.

Our work is related to several recent studies which also examine filer data provided by the OSB. Sarra [2011] examines an OSB sample of filers between 2008 and 2010, and concludes that insufficient income and unemployment accounted for nearly half of the bankruptcies and just over half of consumer proposals. Duncan, Fast, and Johnson [2012] compare the characteristics of 4,000 bankruptcy filers in 2007 and 2010. In addition to some of the variables examined in this paper, they use the “reason for bankruptcy” question, and find that

the fraction of filers reporting unemployment as the main cause of bankruptcy rose between 2007 and 2010.

There is a small but growing literature on the role of unemployment, consumer debt levels and house prices in accounting for cyclical fluctuations in U.S. filings. Bishop [1998] studies the impact of the debt service ratio and (un)employment on filings over 1960-1996. He finds that while the elasticity of bankruptcies with respect to the employment rate is roughly 50% larger than for consumer debt service, the larger variation in the consumer debt service ratio means it is quantitatively more important in accounting for changes in bankruptcies.<sup>8</sup> Garrett and Wall [2013] use state level unemployment rate to construct dummy variables which indicate how many quarters a state has been in recession (expansion). Focusing on the 1998.Q1 to 2004.Q4 period, they find that bankruptcies exhibit a countercyclical pattern, with filings peaking at the end of recessions and slowly declining during the initial quarters of recovery.<sup>9</sup>

A related literature has focused on credit card borrowing and default. Agarwal and Liu [2003] use credit card data over 1994-2001 from a large U.S. financial institution to examine how county-level unemployment rates impact the probability of credit card delinquency, conditional on the account balance, interest rate and borrower characteristics. They find that higher unemployment

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<sup>8</sup>Unfortunately, comparable Canadian data on the DSR is not available, since the Statistics Canada measure only includes interest payments while the U.S. DSR measure includes interest and principal payments.

<sup>9</sup>A related literature examines the factors that account for bankruptcy filings, without disentangling the trend from cyclical fluctuations. VISA USA [1996] found that both employment growth and house prices (among other factors) significantly impacted bankruptcy filing rates. Lockett [2002] reviews several related studies on the U.S. bankruptcy filings.

rates have a statistically significant impact on delinquencies, with an elasticity of roughly 2. In contrast, Gross and Souleles [2002], who look at bankruptcy among a large sample of credit card accounts over 1995-1997, find that risk factors (such as state level unemployment and house prices) play a small role in the rise in bankruptcies. Given the longer time period and the inclusion of a major business cycle in our analysis, it is not surprising that, similar to Agarwal and Liu [2003], we find that both unemployment rates and house prices play a quantitatively significant role in cyclical movements in filings.

The supply channel has received less attention in the empirical literature. Sarra [2011] reports that while few filers report access to credit as the main cause of their filing, there is suggestive evidence that lending standards were tightened (and loan approval rates fell) during the 2008 recession. Allen and Damar [2012] also examine data on Canadian filers over 2007-09, and find that neighborhoods where bank branches closed due to mergers (possibly resulting in the loss of “soft information” on borrowers) experienced higher filings than neighborhoods where branches did not close. They interpret this as suggesting that local supply effects can impact bankruptcy filings.<sup>10</sup> Our paper complements this work by exploring how credit market tightening can impact household decision to file for bankruptcy.

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<sup>10</sup>Less directly related to our work is a large literature on how shocks to the financial sector (particularly banks) impact the real economy. Den Haan and Yamashiro [2009] find that monetary policy shocks have large impacts on consumer lending in Canada.

This paper is organized as follows. Section 3.2 examines the cyclical relationship between aggregate economic indicators and insolvency rates over the past thirty years, and outlines some evidence on changes in lending standards. Section 3.3 examines how the characteristics of filers varied over 2005-2011. Section 3.4 offers a brief conclusion.

## **3.2 Aggregate Data on Insolvency Filing Cycles**

We begin by documenting cyclical movements in insolvency filings at the national and city level. National level data is available annually for most series since the 1970s and quarterly for insolvency since the early nineties. Later, we analyze city level filings with a focus on more recent periods (post 1987) due to data limitations. To distinguish cyclical fluctuations from longer-run trends, we de-trend our data using the HP-filter.<sup>11</sup> This is particularly important since insolvencies have a clear secular trend while several other series (e.g., unemployment) do not.

Our analysis yields three key findings. First, the rise in filings during the most recent recession was similar to past recessions. This is important, as it suggests that insights from our analysis of filer level data are likely to generalize to past recessions. Second, changes in unemployment are closely correlated

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<sup>11</sup>For annual (quarterly) data, we set the smoothing parameter (which governs the trade off between fit and degree of smoothness) to 6.25 (1600) based on Ravn and Uhlig [2002].



with changes in filings. Third, we find suggestive evidence that lending standards – possibly operating partly through changes in household net worth – also play a significant role in cyclical fluctuations.

### **3.2.1 National Data**

Our national analysis documents the correlations between cyclical fluctuations in insolvency filings, unemployment, interest rates, and consumer debt. Where appropriate, we define these terms in the text. Section B.2 contains the data sources used in this paper. The inclusion of unemployment and debt are natural, as income loss is frequently cited as a cause of insolvency, while the discharge of debt is typically the main benefit from filing. As a proxy for credit market conditions, we also include interest rates. Finally, as a proxy for shocks to household balance sheets, where possible we examine the relationship with house prices.

#### **Annual Data: 1966-2011**

Table 3.1 reports the correlations between the cyclical deviations from trend of insolvency filing rate and key aggregate variables, and Table 3.2 reports the corresponding correlations for the growth rates. The consumer insolvency rate is the number of consumer insolvencies per thousand residents aged 18 years

Table 3.1: National Deviation from Trend Correlations with the Insolvency Rate

Years	1966-2011	1977-2011	1980-2011
$\widehat{Unemployment}$	0.29	0.50	0.58
$\widehat{Unemployment}(t - 1)$	-0.28	-0.34	-0.33
$\widehat{Consumer\ Credit / Disposable\ Income}$	-0.07	-0.09	-0.14
$\widehat{Consumer\ Credit / Disposable\ Income}(t - 1)$	0.02	-0.10	-0.21
$\widehat{Mortgage\ Credit / Disposable\ Income}(t)$	-0.19	-0.10	-0.14
$\widehat{Mortgage\ Credit / Disposable\ Income}(t - 1)$	0.08	-0.04	-0.12
$\widehat{Liability / Home\ Equity}$	-0.04	0.18	0.24
$\widehat{Liability / Home\ Equity}(t - 1)$	0.19	0.20	0.22
$\widehat{Bank\ Rate}$	-0.31	-0.37	-0.41
$\widehat{Bank\ Rate}(t - 1)$	0.24	0.34	0.35
$\widehat{Mortgage\ Interest\ Rate}$	-0.01	0.04	-0.02
$\widehat{Mortgage\ Interest\ Rate}(t - 1)$	0.45	0.62	0.69
$\widehat{Consumer\ Interest\ Rate}$			-0.05
$\widehat{Consumer\ Interest\ Rate}(t - 1)$			0.62
$\widehat{Credit\ Card\ Delinquencies}$		0.63	0.63

or above.<sup>12</sup> As can be seen from comparing Tables 3.1 and 3.2, detrending using first differences (i.e., growth rates) yields similar correlations to the HP-filter. While data availability leads us to focus on the 1980-2011 period, we also report correlations for series which are available prior to 1981.

The correlation between the unemployment rate and filings is consistent

<sup>12</sup>Insolvency statistics are only available from 1987 onwards. Prior to the 1992 reforms, proposals were a negligible component of the aggregate insolvency statistic. For this reason, we extend the insolvency series by including using bankruptcy data that goes back until 1966.

Table 3.2: National Growth Rate Correlations with the Insolvency Rate

Years	1966-2011	1977-2011	1980-2011
Unemployment	0.34	0.55	0.57
Unemployment(t-1)	-0.28	-0.39	-0.36
Consumer Credit/Disposable Income	-0.01	-0.01	0.00
Consumer Credit/Disposable Income (t-1)	-0.21	-0.13	-0.08
Mortgage Credit/Disposable Income	-0.16	-0.04	-0.02
Mortgage Credit/Disposable Income (t-1)	-0.19	-0.12	-0.08
Liability/Home Equity	0.00	0.19	0.19
Liability/Home Equity(t-1)	-0.23	-0.14	-0.10
Bank Rate	-0.19	-0.31	-0.36
Bank Rate (t-1)	0.27	0.38	0.37
Mortgage Rate	0.05	0.05	-0.01
Mortgage Rate (t-1)	0.21	0.23	0.21
Consumer Interest Rate			-0.05
Consumer Interest Rate (t-1)			0.38
Credit Card Delinquencies		0.60	0.61

with the view that income shocks are an important factor in many bankruptcies (see Tables 3.1 and 3.3, and Figures 3.2, 3.3 and 3.6). This positive correlation reflects the countercyclical pattern of unemployment and insolvency, as both rise during recessions and decline during expansions (relative to trend). As Figures 3.6 and 3.3 illustrates, this positive relationship was especially pronounced over 2008-2010. The negative correlation between lagged unemployment and insolvency suggests that unemployment rates may decline more quickly when the recession ends than filings.<sup>13</sup> Interestingly, the correlation between unemployment and filings has increased since the late 1970s. This may be due to changes during the 1970s aimed at increasing access to bankruptcy for lower-income consumers (including the unemployed) who would have had trouble arranging a payment option to access the bankruptcy system (Brighton and Connadis, 1982).

We also examine consumer and mortgage debt. Our measures of consumer and mortgage debt come from the national balance sheet (flow of funds). It is important to note that HELOCs are grouped with other lines of credit as part of consumer credit in Canada. Given that the main objective of an insolvency filing is to discharge debt, one might expect fluctuations in insolvencies to track changes in consumer debt levels. However, cyclical movements in consumer credit and mortgage debt relative to disposable personal income are either slightly negatively correlated or uncorrelated with insolvencies (see

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<sup>13</sup>The regression of insolvency (unemployment) deviations on one and two period lagged values of insolvency (unemployment) yields a similar pattern of a positive coefficient on the first lag and a negative coefficient on the second lag.

Tables 3.1 and 3.2).<sup>14</sup> This reflects the fact that consumer borrowing relative to income is slightly pro-cyclical, while insolvencies are countercyclical. From the point of view of simple economic theory, this is counter-intuitive, as one would expect borrowing to increase as households seek to smooth out short-run income declines during recessions. That this does not occur suggests that borrowing becomes either more expensive or less accessible for households during recessions, or that households perceive income shocks during recessions to be persistent rather than transitory. This cyclical pattern of credit access may also reflect household balance sheet effects, as the ratio of liabilities to home equity is counter-cyclical (see Tables 3.1 and 3.2).<sup>15</sup>

Since data on the average (debt-weighted) interest rate of existing and new consumer debt does not exist, we consider three alternative interest rate measures. The first is the Bank Rate, which is closely related to the short term rate at which banks borrow. The second is the average mortgage interest rate, while the third is the prime lending rate for consumer loans. While the consumer loan rate is arguably the best proxy for non-mortgage consumer borrowing costs, it is only available since 1980.

As can be seen from Tables 3.1 and 3.2, average interest rates and current borrowing interest generally have a small negative correlation with insolvencies. This is consistent with the view that interest rates for prime borrowers

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<sup>14</sup>Changes in debt levels may, however, be important in understanding longer run trends in insolvencies, since the secular rise in debt parallels the rise in filings in Figure 3.7

<sup>15</sup>This may be partially driven by cyclical changes in house prices, which can have a large impact on household balance sheets.

Figure 3.6: Annual Unemployment and Consumer Insolvency Rate: Deviations from HP-Trend

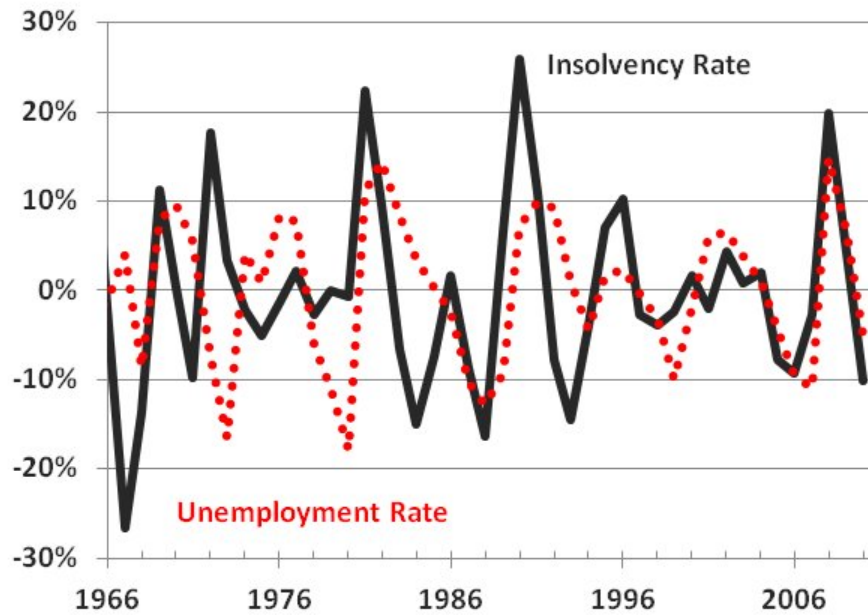
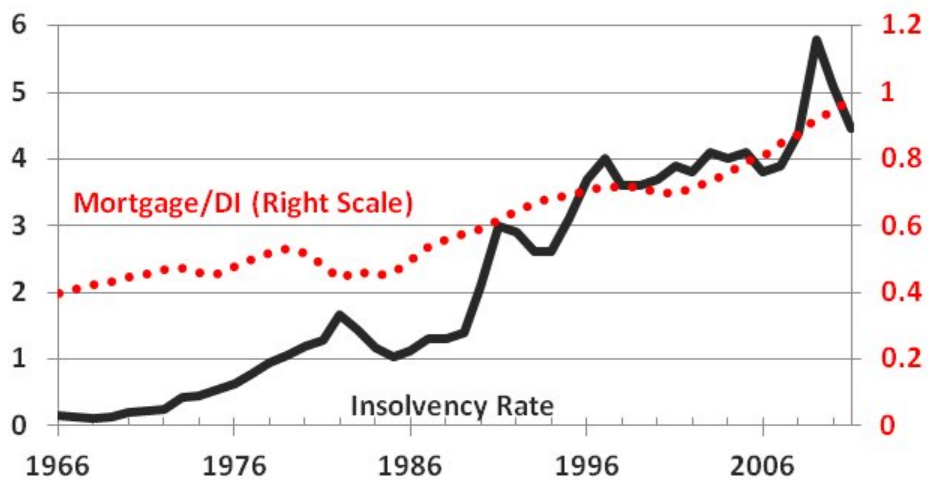


Figure 3.7: Consumer Credit/Personal Disposable Income and Insolvency Rate: 1966-2011



tend to fall during recessions. However, the previous year's interest rate is negatively correlated with insolvencies over the cycles. This may reflect the impact of monetary policy, as short term rates tend to rise near the end of expansions.

The interest rate and debt-income correlations together suggest that changes in access to credit (lending standards) may be important in accounting for cyclical movements in insolvencies. Economic theory suggests that lower interest rates (for low risk borrowers) combined with the incentive to smooth out temporary income declines should result in higher levels of borrowing. That this does not occur suggests that either riskier borrowers face higher interest rates and/or tighter borrowing limits (less access to credit). This mechanism would be consistent with both reduced borrowing, and higher insolvencies as consumers found it more difficult to either roll-over or finance existing debt.

Finally, credit card delinquencies have a high positive correlation with insolvencies. While not surprising, this also suggests that the risk premium for (relatively higher) risk borrowers should increase during recessions. In turn, this higher-risk premium could act to make insolvency more likely for some highly indebted borrowers.

Although this analysis does not examine business related filings, it is worth noting that business related filings rose significantly during the recession. In fact, the fraction of business-related filings increased during (and after) the recent recession.

### 3.2.2 National Level Empirics

We regress the deviation from the H-P trend of the insolvency rate on the ln deviations (denoted by a “hat” – of) contemporaneous and lagged unemployment rates, the prime consumer interest rate, as well as debt-income ratios and housing equity.

We consider several different specifications in Table 3.3. We include both contemporaneous and lagged unemployment, but different combinations of contemporaneous and lagged consumer interest rates and debt-income ratios. Although some of the regressors appear to be insignificant in the last column, they are significant by themselves. To avoid omitted variable bias, we include them in our specification (see column 10 in Table 3.3).



Table 3.3: Determinants of National Annual Insolvency: 1980-2011

	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$	$\widehat{Ins.Rate}_t$
$\widehat{Unemp.Rate}_t$	1.045*** (7.21)	1.084*** (6.7)	0.887*** (5.59)	0.933*** (5.33)	1.115*** (6.23)	1.028*** (6.26)	1.114*** (6.06)	0.976*** (5.83)	1.160*** (6.63)	1.198*** (6.57)
$\widehat{Unemp.Rate}_{t-1}$	-0.808*** (-5.52)	-0.756*** (-4.35)	-0.552** (-2.96)	-0.490* (-2.32)	-0.386 (-1.93)	-0.33 (-1.62)	-0.392 (-1.93)	-0.393 (-1.91)	-0.273 (-1.37)	-0.241 (-1.18)
$\widehat{Cons.Rate}_t$		0.101 (0.57)		0.117 (0.65)	0.374 (1.89)	0.0369 (0.22)	0.31 (1.63)	0.011 (0.06)	0.253 (1.24)	0.294 (1.39)
$\widehat{Cons.Rate}_{t-1}$			0.336* (2.07)	0.344* (2.08)	0.427* (2.73)	0.580** (3.27)	0.402* (2.57)	0.480** (2.82)	0.605** (3.5)	0.656** (3.54)
$\widehat{CC/DI}_t$					1.860* (2.37)				1.297 (0.57)	1.001 (0.43)
$\widehat{CC/DI}_{t-1}$						2.081* (2.51)			1.722* (2.08)	3.529 (1.48)
$\widehat{M/DI}_t$							1.454* (2.18)		0.172 (0.09)	0.425 (0.22)
$\widehat{M/DI}_{t-1}$								2.304 (2.01)		-2.559 (0.81)
$N$	32	32	31	31	31	31	31	31	31	31
adj. R2	0.652	0.644	0.680	0.674	0.721	0.727	0.713	0.707	0.745	0.741

$t$  statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 3.4: Correlations between Annual Variables - 1980-2011 - Deviations from Trend

	Ins. Rate(t)	Unemp Rate (t)	Unemp Rate (t-1)	Cons. Rate (t)	Cons. Rate (t-1)	CC/ DI (t)	CC/ DI (t-1)	Mort/ DI (t)	Mort/ DI (t-1)
Ins. Rate(t)	1.00								
Unemp Rate(t)	0.58	1.00							
Unemp Rate(t-1)	-0.32	0.37	1.00						
Cons. Rate (t)	-0.05	-0.57	-0.61	1.00					
Cons. Rate (t-1)	0.62	0.17	-0.54	0.14	1.00				
CC/DI(t)	-0.14	-0.22	0.11	-0.31	-0.28	1.00			
CC/DI(t-1)	-0.21	-0.55	-0.25	0.45	-0.39	0.23	1.00		
Mort/DI(t)	-0.14	-0.34	-0.02	-0.15	-0.22	0.95	0.28	1.00	
Mort/DI(t-1)	-0.12	-0.50	-0.30	0.52	-0.26	0.14	0.95	0.21	1.00

Table 3.5: Correlations between Quarterly Variables – 1991Q1-2012Q1 – Deviations from Trend

	Bky	q1	q2	q3	UR (t)	UR (t-1)	UR (t-2)	CR (t)	CR (t-1)	CR (t-2)	CC/ DI (t)	CC/ DI (t-1)	CC/ DI (t-2)	M/ DI (t)	M/ DI (t-1)	M/ DI (t-2)
Bky Rate	1.00															
q1	-0.02	1.00														
q2	0.27	-0.34	1.00													
q3	-0.15	-0.34	-0.33	1.00												
Unemp Rate (t)	0.42	0.49	0.04	-0.07	1.00											
Unemp Rate (t-1)	0.35	-0.49	0.51	0.05	0.40	1.00										
Unemp Rate (t-2)	-0.07	-0.13	-0.43	0.51	0.32	0.43	1.00									
Cons Rate (t)	-0.53	0.01	-0.02	0.00	-0.68	-0.63	-0.50	1.00								
Cons Rate (t-1)	-0.37	0.04	-0.02	-0.02	-0.64	-0.69	-0.63	0.87	1.00							
Cons Rate (t-2)	-0.16	0.03	0.01	-0.02	-0.50	-0.64	-0.68	0.66	0.87	1.00						
CC/DI (t)	0.38	-0.37	-0.02	0.20	-0.04	0.29	0.25	-0.28	-0.30	-0.25	1.00					
CC/DI (t-1)	0.29	0.21	-0.34	-0.05	0.13	-0.07	0.22	-0.22	-0.25	-0.27	0.61	1.00				
CC/DI (t-3)	0.34	0.18	0.24	-0.37	0.15	0.10	-0.13	-0.10	-0.20	-0.22	0.36	0.60	1.00			
Mort/DI (t)	0.10	-0.36	-0.06	0.23	0.02	0.35	0.38	-0.31	-0.39	-0.37	0.65	0.26	0.02	1.00		
Mort/DI (t-1)	-0.01	0.17	-0.36	-0.05	0.16	0.02	0.35	-0.28	-0.31	-0.39	0.32	0.65	0.27	0.58	1.00	
Mort/DI (t-2)	0.05	0.21	0.18	-0.35	0.21	0.13	0.00	-0.15	-0.27	-0.31	0.12	0.32	0.65	0.32	0.58	1.00

The coefficient estimates in Table 3.3 are not necessarily a good proxy for the quantitative contribution of different variables to insolvency fluctuations as the covariates are themselves correlated (see Tables 3.1 and 3.2), and differ in their variance. To assess the quantitative contribution, we report a variance decomposition. The first column in Table 3.6 reports the (adjusted) R-squared from the regression of the insolvency rate on each variable alone.<sup>16</sup> Individually, the unemployment rate and the lagged consumer prime rate play the largest role in accounting for fluctuations in insolvencies. However, there is scope for interpretation as to which variable plays the largest role. The last column of Table 3.6 reports the Semi-partial R-squared, which is the R-squared from the regression with all of the variables in Table 3.6 less the R-squared from the regression omitting that covariate.<sup>17</sup> While the contemporaneous unemployment rate and the lagged consumer rate have the most explanatory power, contemporaneous unemployment now accounts for a larger fraction of the cyclical variation in insolvency filings.

To probe the robustness of these findings, we examine the 1990 Q1 to 2012 Q1 period for which we have quarterly insolvency filings. Broadly speaking,

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<sup>16</sup>This specification used maximizes Akaike information criterion.

<sup>17</sup>The partial R-squared indicates how much unique information about insolvency in one covariate is not captured by the other covariates. In this sense, it is a conservative estimate. The partial R-squared indicates the fraction of the maximum possible improvement in  $R^2$  that is contributed by covariate  $k$ .

Table 3.6: Variance Decomposition for National Regression with Annual Data: 1980-2011

Individual Covariate	R <sup>2</sup>	Partial R <sup>2</sup>	Semi-Partial R <sup>2</sup>
Unemp	0.34	0.65	0.40
Unemp(t-1)	0.11	0.13	0.03
Cons Rate (t-1)	0.39	0.32	0.10
CC/DI (t-1)	0.06	0.21	0.05
Mort/DI(t)	0.04	0.08	0.02
All	0.79		

Table 3.7: Variance Decomposition for National Regression with Quarterly Data: 1991Q1-2012Q1

Individual Covariate	R <sup>2</sup>	Partial R <sup>2</sup>	Semi-Partial R <sup>2</sup>
q1	0.00	0.02	0.01
q2	0.06	0.00	0.00
q3	0.02	0.00	0.00
Unemp	0.18	0.06	0.02
Unemp(t-2)	0.55	0.17	0.08
Cons Rate (t)	0.28	0.13	0.06
CC/DI (t)	0.14	0.02	0.01
CC/DI (t-1)	0.08	0.09	0.04
Mort/DI(t-1)	0.00	0.09	0.04
All	0.61		

Table 3.8: Determinants of National Quarterly Bankruptcy: 1991Q1-2012Q1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\widehat{Bk'y.Rate}_t$	$\widehat{Bk'y.Rate}_t$	$\widehat{Bk'y.Rate}_t$	$\widehat{Bk'y.Rate}_t$	$\widehat{Bk'y.Rate}_t$	$\widehat{Bk'y.Rate}_t$	$\widehat{Bk'y.Rate}_t$	$\widehat{Bk'y.Rate}_t$
First Quarter	-0.0379 (-1.02)	-0.0378 (-1.09)	-0.0348 (-1.69)	-0.0369 (-1.65)	-0.0242 (-1.14)	-0.0321 (-1.49)	-0.0289 (-1.41)	-0.0392 (-1.22)
Second Quarter	-0.0142 (-0.33)	0.0146 (0.37)	0.00451 (0.23)	0.00713 (0.33)	0.00477 (0.24)	0.0152 (0.85)	0.0177 (0.88)	0.0334 (0.89)
Third Quarter	0.0173 (0.70)	0.0155 (0.63)	0.0235 (1.14)	0.0286 (1.36)	0.0171 (0.82)	0.0155 (0.81)	-0.00213 (-0.09)	0.00111 (0.05)
$\widehat{Unemp.Rate}_t$	0.657** (3.22)	0.319 (1.57)	0.299 (1.76)	0.402* (2.52)	0.370* (2.38)	0.366* (2.41)	0.577*** (3.82)	0.435* (2.39)
$\widehat{Unemp.Rate}_{t-1}$	0.313 (0.93)	-0.0436 (-0.13)						-0.114 (-0.39)
$\widehat{Unemp.Rate}_{t-2}$	-0.504* (-2.07)	-0.478 (-1.90)	-0.591*** (-3.93)	-0.627*** (-4.55)	-0.542*** (-3.93)	-0.529*** (-3.89)	-0.334 (-1.71)	-0.291 (-1.32)
$\widehat{Cons.Rate}_t$		-0.328** (-3.22)	-0.316*** (-4.53)	-0.246*** (-3.63)	-0.257*** (-3.89)	-0.255*** (-3.98)		-0.323** (-3.33)
$\widehat{Cons.Rate}_{t-1}$		-0.00201 (-0.01)					-0.234* (-2.38)	0.0836 (0.62)
$\widehat{Cons.Rate}_{t-2}$		0.0505 (0.47)					0.173 (1.87)	0.0655 (0.66)
$\widehat{CC/DI}_t$				1.348 (1.58)	1.472 (1.47)	1.131 (1.38)	2.027** (2.96)	0.419 (0.31)
$\widehat{CC/DI}_{t-1}$				0.832 (0.79)		2.455** (2.68)		1.607 (0.93)
$\widehat{CC/DI}_{t-2}$				0.656 (0.78)	2.341* (2.26)		2.046* (2.49)	1.987 (1.46)
$\widehat{Mort/DI}_t$					0.0994 (0.07)			1.299 (0.79)
$\widehat{Mort/DI}_{t-1}$					0.0279 (0.02)	-2.338** (-2.67)		-1.448 (-0.72)
$\widehat{Mort/DI}_{t-2}$					-2.533 (-1.95)		-2.446** (-2.71)	-2.002 (-1.31)
<i>N</i>	85	85	85	85	85	85	85	85
adj. <i>R</i> <sup>2</sup>	0.282	0.405	0.424	0.524	0.556	0.561	0.508	0.553

the results from the quarterly regressions also suggest that movements in unemployment rates and consumer interest rates play a significant role in accounting for insolvencies (see Table 3.8). However, as Table 3.7 shows,<sup>18</sup> with quarterly data it is difficult to robustly identify the quantitative contribution of unemployment, consumer interest rates and debt levels to cyclical movements in insolvency filings.

<sup>18</sup>The appropriate lags in this specification were chosen to maximize the Schwarz Bayesian Information Criterion, and then the Akaike information criterion was used to select the individual covariates.

### 3.2.3 Lending Standards over the Business Cycle

Although direct measures of lending standards are limited, there is suggestive evidence that lending standards tightened during the recession. Credit bureau data provide indirect, but suggestive, evidence that riskier borrowers faced much tighter access to credit during the recent recession. We lack a direct proxy for consumer lending standards.<sup>19</sup>

Instead, we examine credit bureau report data. Credit bureau data provides suggestive insights into how credit availability varied during the recent recession. Services [2012] summarizes information on credit inquiries and credit extended for Canadian consumers. Figure 3.8 shows the growth rate of balances, total limit and the number of accounts from the prior year. Consistent with the aggregate data, the growth in credit balances dropped during the recession. However, credit utilization (balances relative to credit limits) grew during the recession, as the growth of total available credit was half that of balances.

Utilization likely increased during the recession and initial recovery for two reasons. First, some borrowers (perhaps in response to negative income shocks) increased their borrowing using existing credit lines. Second, accounts were closed. It is unlikely that accounts were closed due to less borrower demand since the number of inquiries rose during the onset of the recession. Instead,

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<sup>19</sup>Although not directly related, both the U.S. consumer and Canadian business lending surveys suggested that loan conditions tighten during recessions.

this suggests that lenders moved to tighten credit standards. During the early stages of the recovery, both the number of accounts closed and inquiries fell. Services [2012] indicates that much of the increase in utilization can be attributed to credit cards and unsecured revolving credit, instead of auto finance secured revolving credit and bank installment loans. Moreover, this tightening of lending standards appears to be concentrated amongst higher risk borrowers. Indeed, deRitis, Ackcay, and Kernytsky [2012] report that credit originations for the riskiest borrowers fell by a staggering 50 % during the recession.

It is important to consider this composition effect when interpreting interest rates movements. Figure 3.9 plots the BOC's weekly effective interest and consumer loan rate.<sup>20</sup> During the recession, the consumer interest rate spread over the weekly effective interest rate blew out. This is consistent with lenders perceiving greater risk during the financial crisis.

### **3.2.4 City Empirics**

National unemployment maybe correlated with variables like net worth, which in turn affects insolvency. To explore the role that job-loss plays, we consider 68 city panel in Table 3.9. The idea being that local unemployment conditions are the best proxy for true job-loss, because they are less related to national conditions. Our results are consistent with the national regressions above. In

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<sup>20</sup>The effective interest rate for households is a weighted-average of various mortgage and consumer credit interest rates. The weights are derived from residential mortgage and consumer credit data, adjusted for additional information provided by financial institutions.



Figure 3.8: Credit Availability (Excluding Mortgages): Year-Over-Year Growth

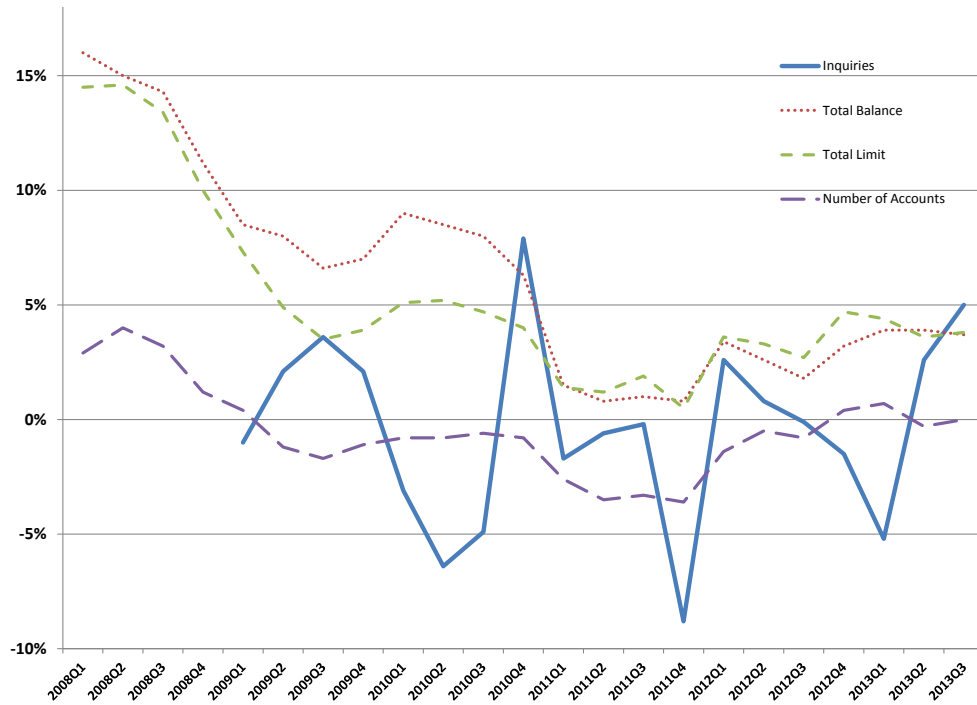


Figure 3.9: Interest Rates: 2007:Q3 - 2011:Q1

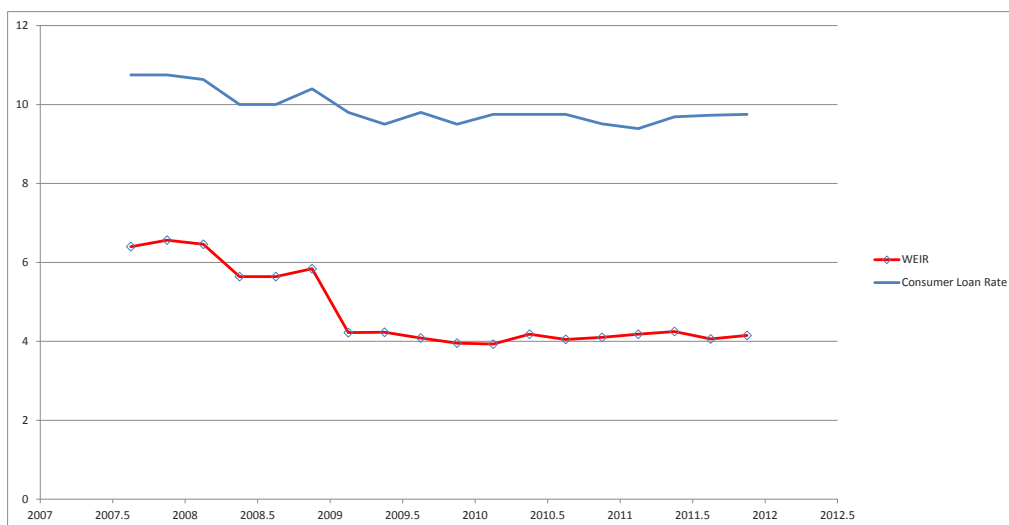


Table 3.9: 68 Cities, annual, 1987–2011

	Ins.Rate <sub>c,t</sub>	Ins.Rate <sub>c,t</sub>	Ins.Rate <sub>c,t</sub>	Ins.Rate <sub>c,t</sub>
Unemp.Rate <sub>c,t</sub>	0.292*** (0.0273)	0.654*** (0.0241)	0.592*** (0.0249)	0.292*** (0.0287)
Unemp.Rate <sub>c,t-1</sub>	0.0982*** (0.0268)	-0.215*** (0.0243)	0.0246 (0.0262)	0.0697* (0.0282)
Cons.Int.Rate <sub>t</sub>	0.345*** (0.0426)		-0.0904* (0.0364)	
Cons.Int.Rate <sub>t-1</sub>	0.366*** (0.0376)		0.648*** (0.0340)	
GDP <sub>t</sub>	-5.722*** (0.288)			-5.508*** (0.242)
GDP <sub>t-1</sub>	0.889** (0.295)			3.331*** (0.245)
<i>N</i>	1600	1600	1600	1600
Adj. <i>R</i> <sup>2</sup>	0.555	0.320	0.445	0.504

fact, if we compare the specification with unemployment, the consumer borrowing rate and their respective lags, we find that total effect of unemployment is near 0.6, while at the national level it is near 0.5 (see the fourth specification in Table 3.3).<sup>21</sup>

## Housing and Insolvency

One factor that could influence a consumer's access to credit is their net worth.

Since home equity is the main asset of many households, changes in house

<sup>21</sup>We also replicated our analysis at the provincial-level using data from same time-period. The total effect of unemployment was higher - at just under 0.8. For brevity, these results are omitted. One reason the total effect might differ is because the provincial regression is weighted by population.

prices could thus significantly impact the amount that households could borrow. This has potentially become even more important, as home equity lines of credits have become an increasing large part of consumer credit in Canada (MacGee [2012]).

To investigate the impact of changes in house prices on insolvency filings, we combine data from the Teranet-National House Price Index for 11 Canadian cities with city insolvency and unemployment rates. Teranet's National Bank House Price Index is a price index based on the repeat sales method (so as to control for quality) for single family homes, and covers eleven Canadian metropolitan areas: Victoria, Vancouver, Calgary, Edmonton, Winnipeg, Hamilton, Toronto, Ottawa, Montreal, Quebec and Halifax. Unfortunately, our house price data is only available for years from 1999 onward.

Table 3.10 shows that city house price growth is negatively related to city insolvency growth rates. This relationship holds even controlling for the consumer lending rate. While one might be concerned that this is simply picking up negative city-level economic shocks, the fact that house prices and unemployment are negatively related for only half of the cities suggests that house prices are not just picking up the effect of changes in households' local employment possibilities.

Table 3.10: Determinants of Annual City Insolvency: 1999-2010

	Ins.Rate <sub>c,t</sub>	Ins.Rate <sub>c,t</sub>	Ins.Rate <sub>c,t</sub>	Ins.Rate <sub>c,t</sub>
Unemp.Rate <sub>c,t</sub>	0.118 (0.0764)	0.308*** (0.0610)	0.292*** (0.0769)	0.116 (0.0781)
Unemp.Rate <sub>c,t-1</sub>	-0.0383 (0.0702)	-0.213*** (0.0488)	-0.248*** (0.0607)	-0.0187 (0.0724)
Cons.Int.Rate <sub>t</sub>	0.286* (0.127)		0.0342 (0.125)	
Cons.Int.Rate <sub>t-1</sub>	-0.217 (0.120)		-0.114 (0.115)	
GDP <sub>t</sub>	-3.621*** (0.694)			-3.009*** (0.618)
GDP <sub>t-1</sub>	1.738* (0.775)			1.343* (0.652)
House Prices <sub>c,t</sub>	-1.379*** (0.168)	-1.489*** (0.176)	-1.555*** (0.190)	-1.312*** (0.170)
<i>N</i>	121	121	121	121
adj. <i>R</i> <sup>2</sup>	0.737	0.653	0.650	0.719

### 3.2.5 Was the 2008 Recession Different?

Before examining the filer-level data in the following section, we ask whether the jump in bankruptcy filings during the 2008 recession is consistent with past recessions. This question is of interest both to evaluate whether the lessons we draw from the micro data likely apply to earlier recessions, and since the rise in consumer debt prior to the Great Recession may have left households more vulnerable to adverse shocks than during previous recessions.

To tackle this question, we generate in- and out-of-sample forecasts for filings. We consider two regression specifications, one which regresses filings on

unemployment (current and lag), the consumer lending rate (lag), and a second which adds (lagged) consumer credit/disposable income.<sup>22</sup> This highlights whether the growth in debt impacts our conditional forecasts for the level of filings, because debt levels are rising over time [MacGee, 2012].

Figure 3.10 plots both out of sample forecast (using annual data up to 2002) and the actual data. Arguably, neither regression provides a good out of sample forecast, as excluding the growth of consumer debt underestimates the jump in filings during the recession, while including growth in debt over-predicts filings in all years since 2002 but the recession.

An alternative approach is to look at the in sample fit for the entire sample (i.e., 1980 to 2012). As can be seen from Figure 3.11, in this case including the growth of consumer debt has little impact on the predicted growth rate of insolvencies. Interestingly, the estimates closely predict the jump in filings during the 2008 recession, but underestimates the growth in filings during the 90-92 recession.<sup>23</sup> Overall, our take-away from this is that the response in filings during the 2008 recession seems in line with past episodes.

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<sup>22</sup>We choose to analyze growth rates, because the HP filter adjusts historical deviations when we include additional data, and thus makes comparisons more transparent.

<sup>23</sup>It is difficult to attribute this episode to consumer debt, income or interest rates. Instead, it is possible that early nineties were subject to much more restructuring of the private sector, which resulted in more long-run joblessness, and consequently insolvencies. For another exposition of this argument, see <http://www.bankofcanada.ca/2001/01/publications/speeches/canada-economic-future-what-have-we-learned/>

Figure 3.10: Out-of-Sample Forecast

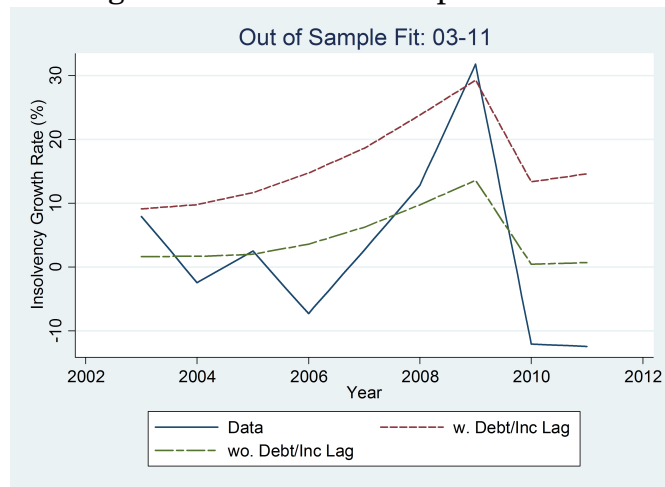
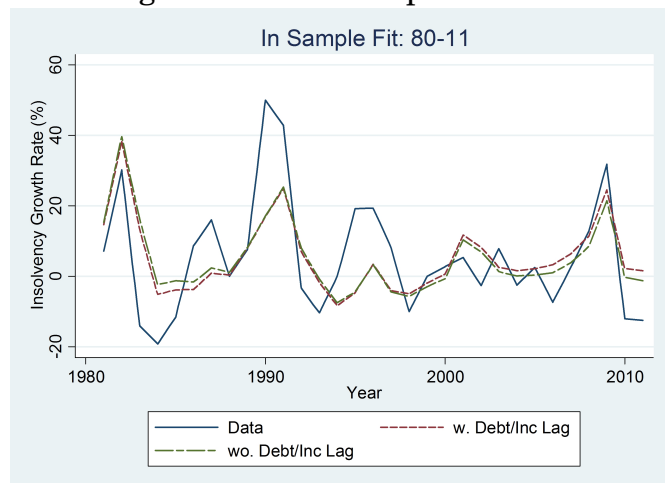


Figure 3.11: In-Sample Forecast



### 3.3 Characteristics of Filers over the Recession

We now turn to unique data on the characteristics of filers collected by the Office of the Superintendent of Bankruptcy (OSB). Our analysis focuses on how the mean and median characteristics of the population of filers evolve over four years: prior to the economic slowdown (July 1, 2007 – June 30, 2008), the onset of the recession (July 1, 2008-June 30, 2009), the initial recovery (July 1 2009 – June 30, 2010) and the continuing recovery (July 1, 2010-June 30, 2011). Although the data period is relatively short, it spans the recent recession. Furthermore, it contains rich details on socio-demographic characteristics, income at the time filing and household liabilities and non-financial assets and

The findings broadly support our analysis of the aggregate data. We find that the fraction of filers reporting they are unemployed rises over 2007-11, and accounts for nearly half of the rise in filings. In addition, the fraction of filers who are homeowners rises, consistent with the negative relationship between house prices and filings. More generally, the filer data indicates that the rise in filings was accompanied by an increase in the number of “middle-class” filers. Besides the rise in homeownership, this is reflected in the rise in the fraction of filers receiving unemployment benefits (suggesting stronger ties to the labour market given the weeks worked required to qualify for unemployment benefits), higher monthly income and debts of filers during the recession, as well as an increase in the number of middle-aged filers.<sup>24</sup> Both the mix

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<sup>24</sup>We compare the filer population to the general population using Statistics Canada data,

of debt (increased share of housing debt) and higher debt levels suggest that many of the filers during the recession had higher pre-recession income levels.

### **3.3.1 Micro Data on Filers**

The database was provided by the OSB, and contains all electronic filings from January 1, 2005 to June 30, 2011, and is based on data collected by Canadian bankruptcy trustees and proposal administrators from filers. The data is mainly collected on two required forms in the Bankruptcy and Insolvency Act: Form 79, the Statement of Affairs (Non-Business Bankruptcy/Proposal), and Form 65, the Monthly Income and Expense Statement of the Bankrupt/Debtor and the Family Unit and Information (or Amended Information) Concerning the Financial Situation of the Individual Bankrupt. Our data include socio-demographic characteristics (age, family size), income at the time of filing and detailed data on households' debts and assets.

The availability of these data reflects the move to electronic from “paper” filings. While in 2005 only 56.6% of all filings were filed electronically, by 2007 (2009) 96% (99%) of all filings were completed electronically. Thus, our sample includes nearly all filers immediately prior to and since the beginning of the most recent recession. Our dataset contains information on 669,153 insolvency filings made electronically from January 1, 2005 to June 30, 2011 (out of

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and find that these changes are not driven by shifts in the characteristics of the Canadian populace. We hope use the Survey of Labour and Income Dynamics to compare the population of filers to the general population, but the release of necessary data is several years behind the OSB and not available at the time of writing.



735,311 total filings). Overall, the quality of the dataset (for the questions we use) is quite good, and there are few missing observations.<sup>25</sup> For example, age and gender are each omitted from less 0.02% of applications.

The sample we analyze contains 517,651 insolvency filings: 404,511 bankruptcies and 113,140 consumer proposals. Under a consumer proposal, an insolvent individual typically pays back more of the debt. In return, they are granted more flexible terms, and they have a better credit report.<sup>26</sup> Of the proposals during this period, 110,158 were Division II debtors, and 2,982 were Division I debtors.<sup>27</sup>

Since the project focuses on consumer insolvencies, 22,570 filings that were classified as business are removed from the sample. The classification is determined by whether the majority of filer's debt is consumer or business related, as attributed by the trustee or administrator. Even if business debt is not the primary debt on the balance sheet, it may have contributed to the insolvency. For this reason, 128,242 individuals who indicated they ran a business in the last five years were removed. Finally, there are several records with exceptionally high liabilities, whose inclusion materially changes the average debt level of filers in a quarter. To address this, 690 filers with liabilities exceeding \$1,000,000 are dropped from our sample.

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<sup>25</sup> One exception is the assets and liabilities of filers, which code zero as missing values.

<sup>26</sup> There are also limitations to some professionals if they file for bankruptcy.

<sup>27</sup> Division I occurs when the debts are greater than \$250,000, where Division II occurs when debts are less than this amount.

### **3.3.2 Insolvency Filings between 2007 and 2011**

Before examining shifts in the distribution of filers, we briefly summarize several key aggregate measures. Given the substantial seasonality in the data, we report the evolution of filings over one-year periods. To mitigate concerns about sample selection, we focus on the 4 years starting in July 1, 2007 and ending June 30, 2011.<sup>28</sup> The first year (July 1, 2007 - June 30, 2008) precedes the recession, while the second coincides with its onset, and the last two (July 1, 2009 - June 30, 2010 and July 1, 2010 - June 30, 2011) the slow recovery.

As can be seen from Table 3.11, insolvency filings initially rose and then leveled off over these years. Comparing the growth rates from year to year, insolvency rate rose by 29%, 5% and -12% in the second, third and fourth years, respectively. Bankruptcies initially rose quicker than proposals, although proposals share of total filings continued. This trend may reflect the 2009 bankruptcy reform, as proposals continued to rise during 2010 and 2011 even as bankruptcies declined.

### **3.3.3 Income**

In this section, we document how filer income compares to the general population over the four-year period. Due to the data reporting windows used by Statistics Canada, this analysis focuses on calendar years.

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<sup>28</sup>One concern may be that trustees that switched to electronic filings later may be concentrated in some geographical regions.

Table 3.12 compares the nominal net-income of filers and the general population. While insolvency filers income tends to be well below the population average, the gap narrowed during the recession.<sup>29</sup> In 2007, unattached individuals earn about two-third of their counterparts in the general population. The income differences are much larger for filers with families, who earn just over two-fifths of the average non-filer's income.

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<sup>29</sup>While reported incomes are substantially less than the general population, more work must be done to understand the income levels prior to filing. In Section B.1 we make progress in this endeavor by inferring income using the characteristics of filers.

Table 3.11: Annual Filing Rates from July 2007 to June 2011

Period	Insolvency Rate	Consumer Proposal Rate	Bankruptcy Rate
07/2007-06/ 2008	3.99	0.86	3.13
07/2008-06/ 2009	5.14	1.12	4.02
07/2009-06/ 2010	5.38	1.48	3.90
07/2010-06/ 2011	4.73	1.61	3.11

Table 3.12: Average Family Net-Income

Year	All Family Units			Unattached Individuals			Families		
	Filers (\$)	Pop (\$)	Ratio (%)	Filers (\$)	Pop (\$)	Ratio (%)	Filers (\$)	Pop (\$)	Ratio (%)
2007	25861	59190	43.7	19472	30599	63.6	32186	74107	43.4
2008	27287	61408	44.4	20212	31830	63.5	34177	76883	44.5
2009	28539	61766	46.2	20613	32307	63.8	35564	77281	46.0
2010	29493	63000	46.8	21077	33000	63.9	36574	78800	46.4

Source: OSB and Cansim Table 202-0603. Family members income is counted even if the application is not joint.

Table 3.13: Median Total Nominal Income

Year	Filer Net Total Income	Taxfiler and Dependent Total Income	Ratio (%)
2007	24,084	27,960	86.1
2008	24,096	28,920	83.3
2009	24,108	28,840	83.6
2010	24,120	29,250	82.5

Source: OSB and Cansim Table 111-0008.

Table 3.12 documents what might seem surprising – the rise in filings during the recession saw the gap between the average income of filers and non-filers narrow. This suggests that the recession may have pushed more “middle-class” filers into insolvency. This is consistent with the changes in composition of families (discussed in the next section) or changes in the types of families filing for insolvency. Income growth amongst the population of unattached filers appears to be keeping pace with the income growth amongst unattached individuals in the population. However, income growth of families filing for insolvency was greater than the general population. As a result, the gap between filing families and the general population appeared to close over the recession. This effect was amplified by the fact that the filers with families grew faster than did unattached filers during the recession.<sup>30</sup>

An examination of median income also suggests a shift in the composition of filers during the recession. Comparing median incomes to the general population is difficult, since Statistics Canada median income measure is gross income for taxfilers with dependents.<sup>31</sup> Table 3.13 comparison median incomes.

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<sup>30</sup>It is worth noting that current filer incomes are lower (relative to mean household income) than previous Canadian studies, suggesting that the average income of the typical bankrupt may have fallen over the past twenty years. Schwartz [1999] reports mean (median) income of bankrupts of \$35,271 (\$29,575), while Brighton and Connadis [1982] reports mean pre-tax income of \$36,583 (all in 2007 dollars). However, these values should be interpreted with care. In both surveys a number of respondents did not report income, and most respondents in 1977 listed their net (post-tax) income. The mean net income was only 65% of the gross mean, which suggests that the true mean income could have been even lower in 1977.

<sup>31</sup>A dependent is a member of a family who did not file a personal income tax return for the referenced year.

Table 3.13 shows how insolvency filer income changes differed from tax filer incomes. While we see virtually no nominal growth in median incomes amongst filers, median incomes for the Canadian population did continue to grow. Comparing this pattern against the one in Table 3.12 suggests that higher income families are responsible for the growth in filer income.

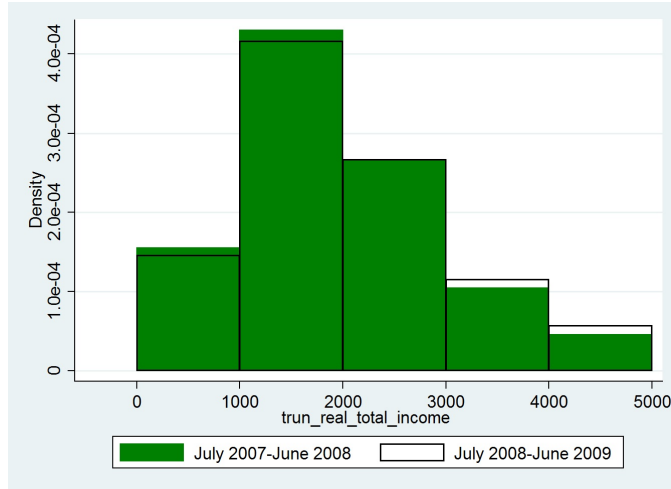
While average income provides considerable insight, changes in the distribution of filer income provides additional information into the dynamics of bankruptcy over the business cycle. To further understand distributional income changes, we plot net-income histograms of filers for each year. Figure 3.12 suggests that while the distribution of filer earnings across the past four years is similar, there has been a slight increase in the fraction of (relatively) higher income filers.

### **Projected Income**

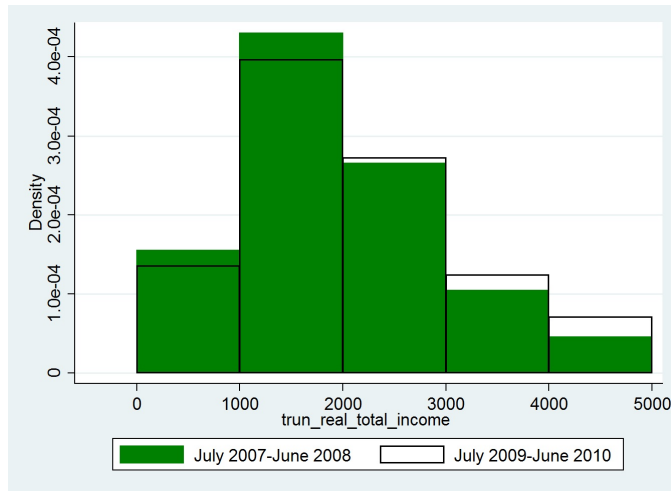
While our data provides rich details on socio-demographic characteristics, income at the time filing, and household liabilities and non-financial assets, we lack information on filer's earnings history prior to the filing. This complicates the interpretation of changes in filer income during the recession, as this may hide larger deviations from "regular" income due to unemployment.

To address this, we use data from the 2005 Survey of Financial Security

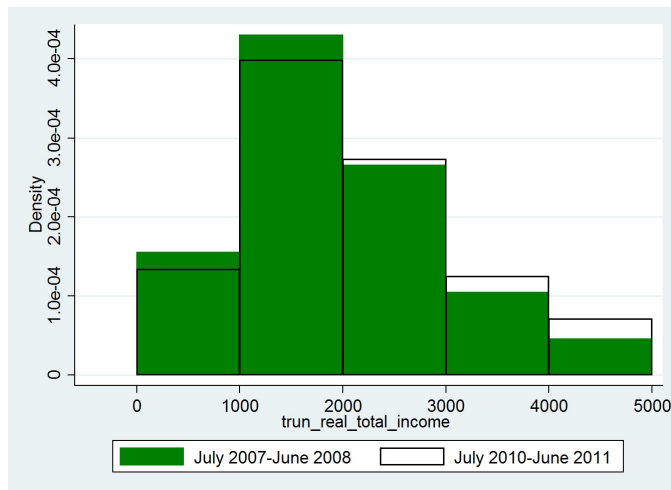
Figure 3.12: Real Monthly Family Income Distribution Relative to 07Q3-08Q2



(a)



(b)



(c)

to estimate the relationship between household characteristics and total net-family income.<sup>32</sup> We then use the estimated coefficients to impute the expected income levels of filers, which we scale by mean income growth (see the Appendix B for more details on our imputation procedure).<sup>33</sup>

Figures 3.13 and 3.14 plot the mean projected income and the mean reported income, by age cohort, for filers with and without mortgage debt, respectively. Comparing the two plots, provides two insights. First, filers without mortgage debt have lower average income than those with mortgage debt. This is not surprising, since homeowner's income is typically higher (on average) than renters. What is surprising is the different gaps between projected income and reported income for filers with and without mortgage debt. For filers without mortgage debt, the gap between projected and reported income is small, and there is no trend over the recession. In contrast, the projected income of filers with mortgage debt is well above their reported income, with a larger gap for older households. This suggests that income shocks may be a significant contributor to filings, particularly for homeowners. The second is that the gap between income and filing and our projected income widens during the recession, before narrowing as filings decline.

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<sup>32</sup>This is the only common income variable between our OBS data and the SFS.

<sup>33</sup>Due to issues with selection, one should be cautious in interpreting levels. However, our primary interest is related to the changes in the projection of income which should be less influenced by any change in selection.



Figure 3.13: Projected Income with Mortgage Debt

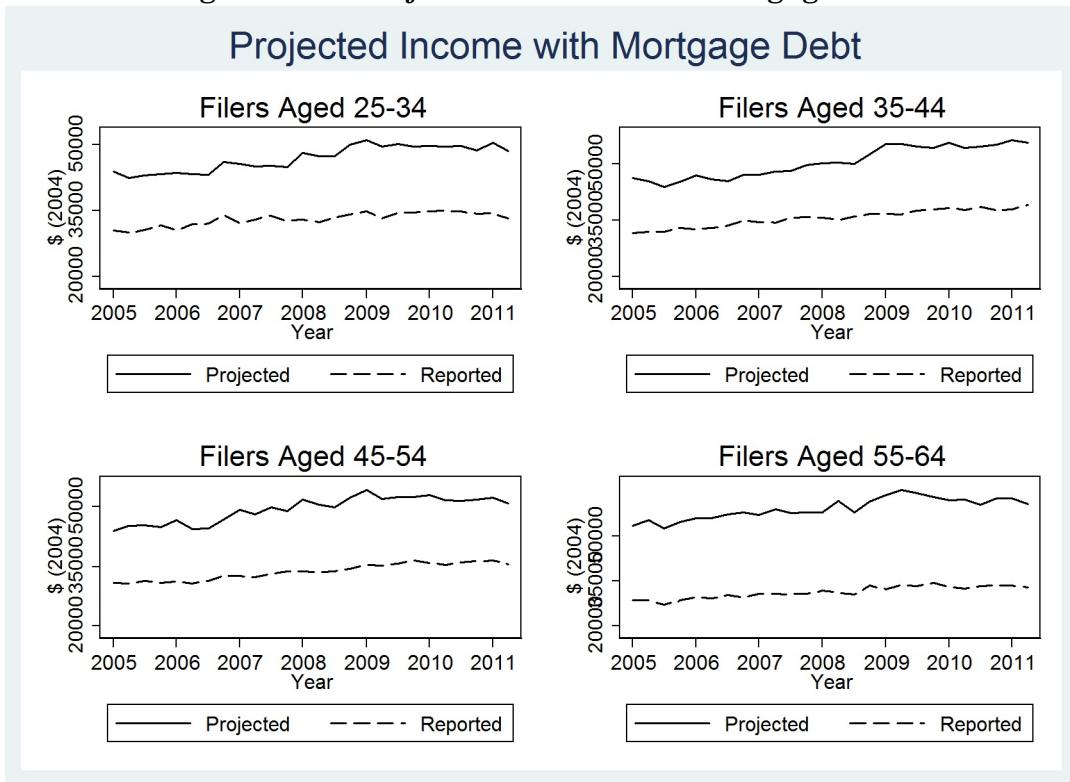
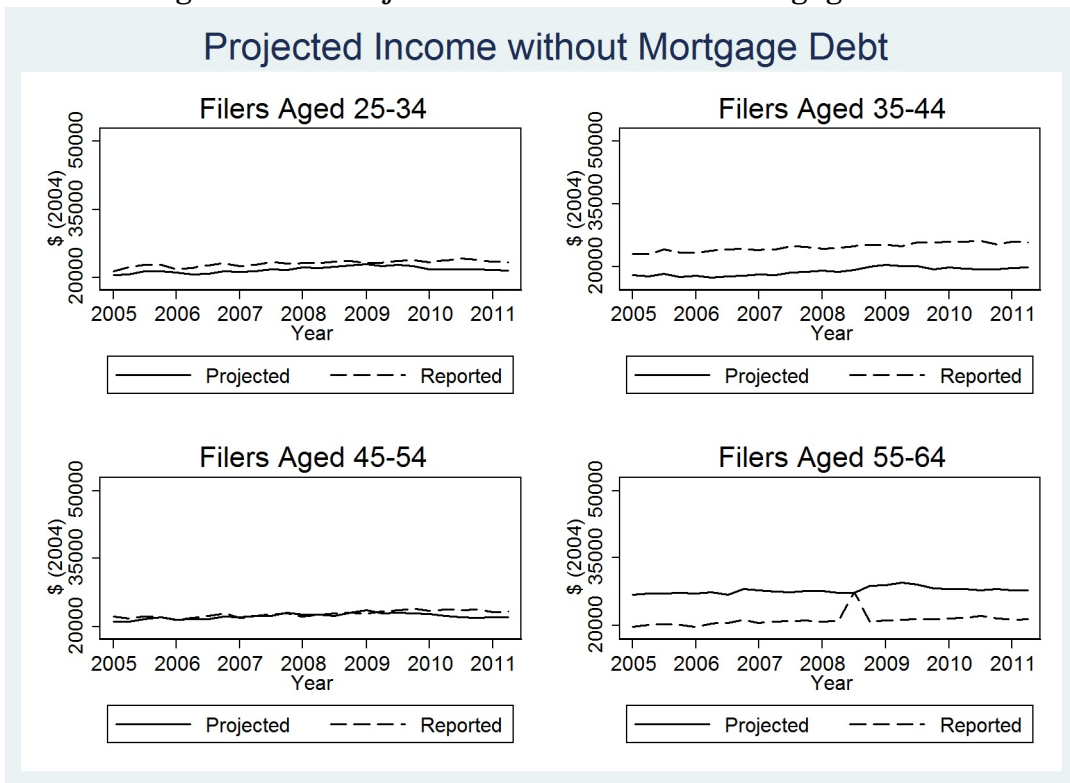


Figure 3.14: Projected Income without Mortgage Debt



### 3.3.4 Employment

To investigate the role of unemployment, we examine two income components reported by filers: whether the filer reports employment insurance (EI) income, and whether the filer reports zero labour earnings (which we categorize as unemployed). Table 3.14 shows that the fraction of filers receiving EI tracks the rise and decline in both the filing rate and the unemployment rate (compare with Figure 3.3). Interestingly, the fraction of unemployed filers, (i.e. filers reporting zero income) also rises. This is consistent with the view that one factor in the high levels of filings in 2010 and 2011 may have been prolonged spells of unemployment which resulted in the exhaustion of EI benefits.

Table 3.15 shows the direct contribution from filers who we classify as unemployed. In our sample, the rise in the total number of filers ranged between 16,638 and 27,626 from the year prior to the recession. Similarly, the rise in the total number of filers which we classify as unemployed appears to be about 8,206-12,473. Taken together, unemployed filers account for nearly half of the total rise in filers. There are two factors which suggest this may be a lower bound estimate of the contribution of job loss. First, this measure does not capture individuals who lost a job but then obtained new employment at lower levels of income. Second, there are other factors, such as lending standards, which may be disproportionately affecting individuals who have lost their job. We return to the impact of lending standards in Section 3.2.3.

Table 3.14: Labor Force Statistics of Filers

Period	Fraction Receiving EI (%)	Fraction Unemployed (%)
07/2007-06/ 2008	7.1	34.2
07/2008-06/ 2009	8.7	35.5
07/2009-06/ 2010	9.4	36.5
07/2010-06/ 2011	7.9	36.7

Table 3.15: Contribution from Unemployment

Time Period	Filers w. No Emp. Income or Collect EI	Total Filers	Contribution (%)
07/2007-06/2008	27040	77122	
07/2008-06/2009	36320	99621	41
07/2009-06/2010	39513	104748	45
07/2010-06/2011	35246	93760	49

Table 3.16: Filer Age

Period	Age
07/2007-06/ 2008	42.9
07/2008-06/ 2009	43.3
07/2009-06/ 2010	44.3
07/2010-06/ 2011	45.5

### 3.3.5 Demographic Characteristics of Filers

The data offers considerable details on filer's socio-demographic characteristics. To the extent that household characteristics such as home ownership and age are correlated with average lifetime earnings, these data also suggests that a larger fraction of filers during the recession are from the "middle-class".

#### Age

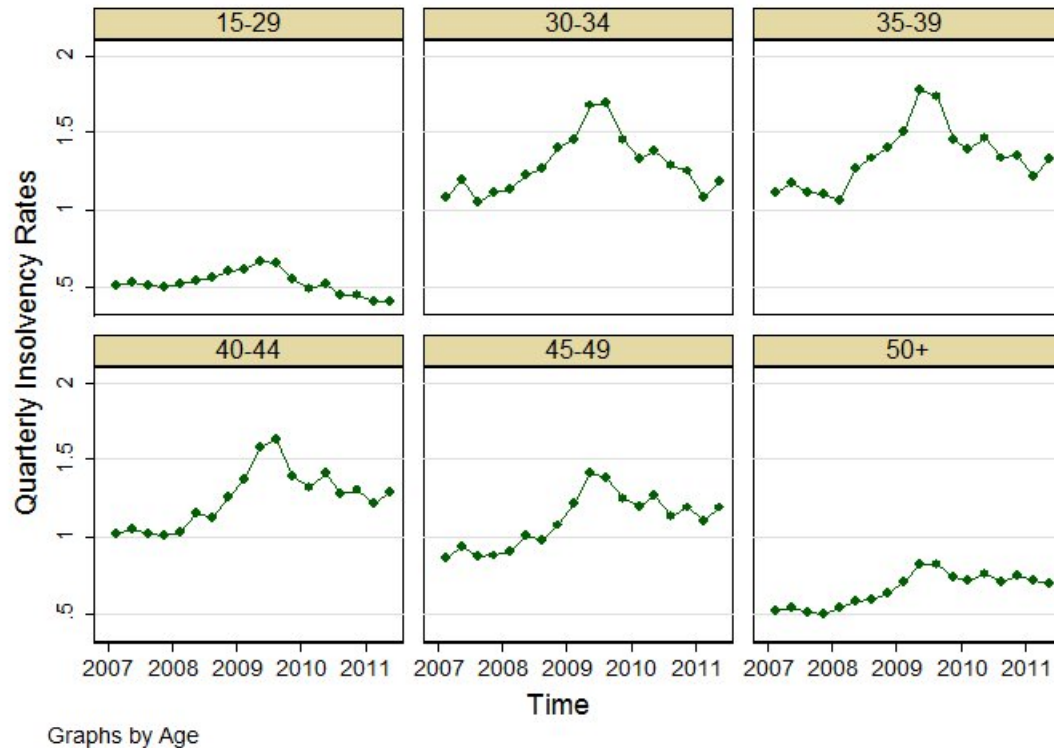
The average age of filers rose during the recent recession, with a cumulative increase of 6% (see Table 3.16). The aging population was a minor contributor, as the median age in the general population rose from 39.2 to 39.9 (less than a 2% increase) from 2007 to 2011.<sup>34</sup> Instead, filer age increased for two reasons: (1) middle aged households seem to have been especially impacted by the recession; and (2) a long-run trend towards (more) older filers.

The contribution of middle-aged households to the rise in insolvency filings can be seen from the plots of filing rates by age cohorts in Figure 3.15. Not only did the older middle aged cohorts filing rates rise, but they have also declined less quickly during the initial years of the recovery. This is consistent with the view that some households faced persistent earnings shocks or prolonged spells of unemployment. The 45 to 54 age cohort performed particularly poorly, as they were the only cohort to see a decline in average real income relative to 2007 (see Table 3.17). Furthermore, this cohort also experienced the largest

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<sup>34</sup>See Cansim Table 051-0001.

Figure 3.15: Insolvency Rates by Age Cohort



and most sustained rise in unemployment. Compared to previous studies of Canadian bankrupts by Brighton and Connadis [1982] and Schwartz [1999], our data suggests a longer run trend towards filings by older bankrupts (see Table 3.18).

The shift towards older (working-aged) filers is a likely factor in the shift towards more “middle-class” filers. Table 3.19 shows that age and unemployment amongst different age cohorts in the general population. In general, income increases with age until ages above 55. Similarly, unemployment decreases until

Table 3.17: Age Cohort Labour Force Attachment Relative to 2007

Age Cohort	Relative Income				Relative Unemployment			
	2008	2009	2010	2011	2008	2009	2010	2011
20 to 24 years	1.04	1.02	1.01	0.98	1.02	1.39	1.33	1.26
25 to 34 years	1.03	1.01	1.03	1.03	0.98	1.39	1.36	1.23
35 to 44 years	1.03	1.03	1.04	1.06	0.99	1.36	1.33	1.17
45 to 54 years	1.02	0.98	0.99	0.98	1.04	1.44	1.39	1.27
55 to 64 years	0.99	1.03	1.02	1.02	1.08	1.38	1.32	1.32

Source: Cansim Tables 202-0407 and 282-0001.

Table 3.18: Age Profile of Bankrupts: Canada

Age	18-29	30-49	50 +	avg.
1977	0.90	1.10	0.21	0.78
1994	1.98	3.92	0.98	2.45
1997	5.20	4.59	1.49	3.74

Source: 1977 is from Brighton and Connadis [1982], 1994 is from Ramsay [1999] (Ontario only), while 1997 is from Schwartz [1999]. The filing rate is per 1000 18 and above, and is for consumer bankruptcies only (consumer proposals in 1997 were not included).

Table 3.19: Income and Employment by Age in 2007

Age Group	Average Income of Recipients	Unemployment
20 to 24 years	17003	8.68
25 to 34 years	35956	5.67
35 to 44 years	45805	5.11
45 to 54 years	50172	4.47
55 to 64 years	41067	5.04

Source: Cansim Tables 202-0407 and 282-0001.

ages above 55.

### Age and Filing during Recessions

The lag between rising unemployment and the rise in filings differs by age cohort. To examine this, we construct a provincial panel as any national panel is too short in time and unemployment by age-cohort is not available at the city level. We regress the quarterly provincial insolvency rate on current and lagged provincial unemployment rates for five year age cohorts from 2007Q1 to 2011Q2:

$$\widehat{\text{Insolvency Rate}}_{t,p,a} = \widehat{\text{Unemployment Rate}}_{t,p,a} + \widehat{\text{Unemployment Rate}}_{t-1,p,a} + \epsilon_{t,p,a}.$$

The regression estimates (see Table 3.22) indicate that filing rates of older filers are more responsive to lagged unemployment rates than younger filers. Strikingly, the coefficient on lagged unemployment is not significant at the 10% level for households below 50, but is for older households.

### 3.3.6 Gender

The recession saw a quickening of the trend towards an increase in the fraction of female filers.<sup>35</sup> Indeed, as Table 3.21 shows, during the recovery from the recession, there were more females than males amongst primary filers.

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<sup>35</sup>During our sample, the average Canadian working female earned between 64.3 and 68.6 compared to the average male.<sup>36</sup> Schwartz (1999) reports that the median debt to income ratio of single men was 1.36 and for women 1.31. However, the median unsecured debt to income ratio was 1.16 for women versus 0.93 for men. Single women also had larger families than did single men.

Table 3.20: Unemployment and Insolvency Rate - Age Cohorts: 07Q1-11Q2

	Ages 25-29	Ages 30-34	Ages 35-39	Ages 40-44	Ages 45-49	Ages 50-54	Ages 55-59	Ages 60-64
q1	-0.0524* (-2.40)	-0.0783*** (-4.04)	-0.0662*** (-3.65)	-0.0704*** (-3.89)	-0.0459** (-2.66)	-0.0298 (-1.56)	-0.0223 (-1.25)	0.00427 -0.21
q2	0.0206 (-0.98)	0.0389* (-2.09)	0.0484** (-2.74)	0.0362* (-2.08)	0.0548** (-3.23)	0.0047 (-0.27)	0.0185 (-1.1)	0.00359 (-0.18)
q3	0.0153 (-0.7)	0.0192 (-1.02)	0.0168 (-0.86)	0.013 (-0.75)	-0.00946 (-0.53)	0.00564 (-0.31)	0.0209 (-1.17)	0.0095 (-0.46)
$\widehat{Unemp.Rate}_t$ Ages 25-29	0.333*** (-4.48)							
$\widehat{Unemp.Rate}_{t-1}$ Ages 25-29	-0.0188 (-0.24)							
$\widehat{Unemp.Rate}_t$ Ages 30-34		0.408*** (-6.68)						
$\widehat{Unemp.Rate}_{t-1}$ Ages 30-34		0.0807 (-1.25)						
$\widehat{Unemp.Rate}_t$ Ages 35-39			0.368*** (-6.17)					
$\widehat{Unemp.Rate}_{t-1}$ Ages 35-39			0.11 (-1.75)					
$\widehat{Unemp.Rate}_t$ Ages 40-44				0.383*** (-7.18)				
$\widehat{Unemp.Rate}_{t-1}$ Ages 40-44				0.103 (-1.74)				
$\widehat{Unemp.Rate}_t$ Ages 45-49					0.341*** (-5.91)			
$\widehat{Unemp.Rate}_{t-1}$ Ages 45-49					0.0537 (-0.9)			
$\widehat{Unemp.Rate}_t$ Ages 50-54						0.316*** (-5.68)		
$\widehat{Unemp.Rate}_{t-1}$ Ages 50-54						0.145* (-2.5)		
$\widehat{Unemp.Rate}_t$ Ages 55-59							0.353*** (-6.37)	
$\widehat{Unemp.Rate}_{t-1}$ Ages 55-59							0.252*** (-4.44)	
$\widehat{Unemp.Rate}_t$ Ages 60-64								0.105 (-1.95)
$\widehat{Unemp.Rate}_{t-1}$ Ages 60-64								0.184** (-3.29)
N	180	180	180	180	180	180	180	180
adj. R <sup>2</sup>	0.106	0.317	0.27	0.322	0.273	0.261	0.297	0.083

Dependent variable is the HP-filtered insolvency rate for the respective age cohort. Regressions are weighted by provincial population.  $t$  statistics in parentheses.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$



This relative decline in male filers reflects a longer term trend. Figure 3.16 plots the fraction of all female filers over time and fits a quadratic function that accounts for seasonality. Unlike Table 3.22 which uses the gender of the primary filer, in Figure 3.16 we account for the gender of the second filer in joint filings. While the shift towards female filings is visible prior to the recession in our data, it is worth noting that the pre-recession share of female filers is well above the roughly 30% estimate reported by [Brighton and Connadis, 1982] for 1977, or the [Schwartz, 1999] estimate of 40% in 1997.<sup>37</sup>

The trend towards more female filers seems to have accelerated during the recession. This may seem puzzling in light of popular discussions of a “man-recession”, which focused on the greater sensitivity of males cyclical income risk. Indeed, male unemployment jumped by 3% points from 2007 to 2009, while female unemployment only jumped by 1.4% points.<sup>38</sup> However, as discussed in the next section, significant changes in family structure interact with gender differences in unemployment dynamics.

### 3.3.7 Family Structure

Filers are less likely to be in a permanent relationship than the typical Canadian. While 62% of Canadians cohabited in 2004 (based on the SFS 2005), during the four years of our filer sample the highest rate of cohabitation was 40% (see Table 3.22). However, the fraction of cohabiting filers including those with children rose during the recession, with a corresponding decline in the

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<sup>37</sup> A similar trend in the change of filer gender is found in United States (see Livshits, MacGee, and Tertilt [2010]).

<sup>38</sup> See Cansim Table 282-0086.

Figure 3.16: Fraction of Female Filers



Table 3.21: Gender of Primary Filers

Period	Male
07/2007-06/ 2008	51.7%
07/2008-06/2009	50.6%
07/2009-06/ 2010	49.6%
07/2010-06/ 2011	48.9%

fraction reporting being divorced or single. This pushed the family structure of filers closer to the general population, and again suggests a rise in the number of middle-class filers during the recession. Table 3.23 indicates that the rise in female filers was driven by more married couples filing and more single women, with the share of single male filers declining.

Table 3.22: Family Structure of Primary Filers

Period	Cohabitation Rate	Formerly Married	Single	Cohabiting if Kids
07/2007-06/ 2008	36.3	30.5	33.2	60.1
07/2008-06/ 2009	38.4	29.3	32.3	61.5
07/2009-06/ 2010	40.0	29.0	31.0	62.9
07/2010-06/ 2011	39.4	29.8	30.8	61.5

Table 3.23: Male Fraction

Period	Fraction of Males		
	Cohabitation	Formerly Married	Single
07/2007-06/ 2008	53.8	43.7	56.2
07/2008-06/2009	52.4	42.9	55
07/2009-06/ 2010	52.2	41.8	53.1
07/2010-06/ 2011	52.0	40.1	52.0

Table 3.24: Family Status of Bankrupts in Canada

	Year	Married/Cohabiting	Formerly Married	Single
Bankrupts	1977	70	22	8
Pop 15-64	1976	64	6	30
Bankrupts:	1997	43	29	28
Pop 15-64:	1995	60	7	32

Source: Schwartz [1999].

The family structure of filers in Canada has remained fairly constant since 1997. However, prior to that date there seemed to be more dramatic changes. As Table 3.24 reports, married (including common law) couple's share of bankruptcies has fallen below their share of the Canadian population. Interestingly, the number of filers without dependents has increased slightly, from 38 percent in 1977 to 46 percent in 1997, and to a relatively constant 52 percent during our sample.

### **3.3.8 Filer Balance Sheet: Changes in the Composition of Debts and Assets**

Filers have lower net worth and fewer assets than the typical Canadian household. The median asset of a Canadian family unit (household) in 2004 was \$229,900, and the median debt was \$44,500 (Survey of Financial Security 2005). While one expects filers to have negative net worth, Table 3.25 highlights the fact that filers also have much lower holdings of assets. In addition, the debts of the median filer are lower than that of the median Canadian family unit. This points towards the fact that many filers are both income and wealth poor, and likely have lower long term income prospects than many Canadian households.<sup>39</sup> However, the higher mean debt reported in Table 3.25 implies that population of filers also includes a number of households with income prospects closer to that of middle-class Canadians.

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<sup>39</sup>The correlation between debt and income is 0.33 in 2005 SFS.

The average liabilities and non-financial assets of filers rose during the recession, with most of the jumps coinciding with the rise in filings. Table 3.25 shows that this was driven by a subset of filers, as the median total liability grew much less than the average liability. This was not the case for the unsecured liabilities, which points to the role of homeowners in driving the rise in mean filer debt. This is suggestive of middle-class filers becoming more predominant in the pool of filers, because they have much higher assets and income than the typical filer.

Table 3.25: Filer Balance Sheet Characteristics

Period	Total Liabilities			Total Unsecured Liabilities			Assets		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
07/2007-06/ 2008	66533	34747	85676	38571	28681	42071	33202	1978	75290
07/2008-06/ 2009	83636	39618	106511	42109	31449	43882	47193	3000	94114
07/2009-06/ 2010	92873	42782	115525	43835	32615	44718	55561	3701	104782
07/2010-06/ 2011	94790	43251	117917	44099	32730	44881	57798	3800	107346

Table 3.26: Filer Net Worth

Period	Net Worth <sup>40</sup>			Net Worth to Income	
	Mean	Median	Std. Dev.	Mean	Median
07/2007-06/ 2008	-33332	-25250	46133	-15.1467	-12.4844
07/2008-06/ 2009	-36443	-27446	47230	-15.5754	-12.9339
07/2009-06/ 2010	-37311	-28046	50117	-15.343	-12.7171
07/2010-06/ 2011	-36992	-27775	49229	-14.8118	-14.8118

From Table 3.26, we see that the combined growth in assets and liabilities led to a moderate rise in mean and median negative net worth. As Figure 3.17 illustrates, there was little trend over the recession in terms of the ratio of net worth to income. However, total debt relative to income rose during the recession. This suggests that the typical filer during the recession was under even more financial “pressure” than they were prior to the recession. The higher debt to income ratio is also consistent with a larger fraction of middle class filers who had experienced a recession related income shock entering the pool of filers.

### **Home Ownership**

Home-ownership is a particularly interesting measure, as it is traditionally associated with middle-class membership. Table 3.27 shows the dynamics of the number of filers reporting home ownership or mortgage debt. Strikingly, close to 65% of the rise in filings can be attributed to filers who own homes or have mortgage debt. This is particularly striking given that the relatively few filers before the recession were homeowners.

### **3.3.9 Student Loans**

Unfortunately, data on the education of level of filers is not collected. Filers do, however, report detailed data on the composition of their debt. We use this data to compute the fraction of filers with at least \$1,000 in student debt by age cohort. As can be seen from Figure 3.18, the fraction of filers in their

Figure 3.17: Filers: Net Worth to Income Ratio

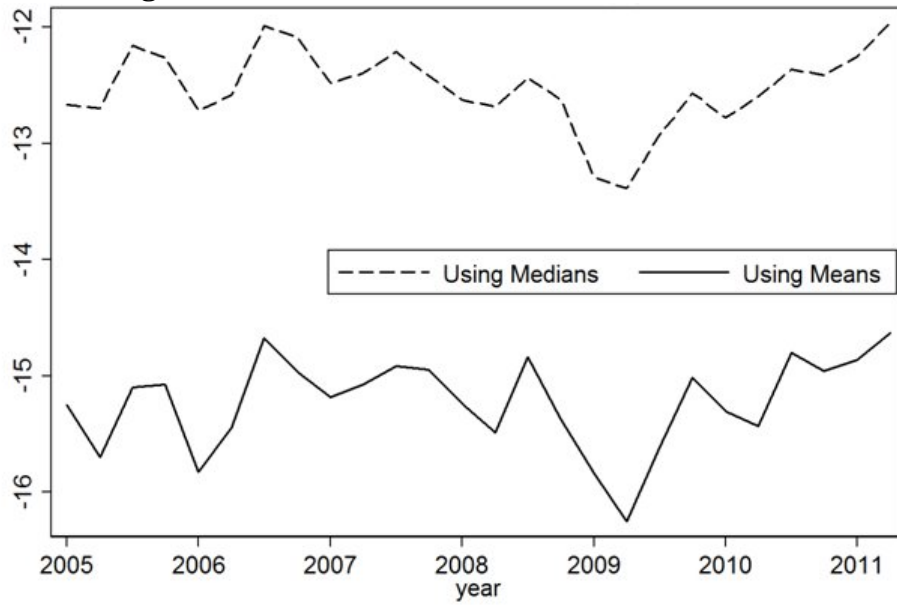
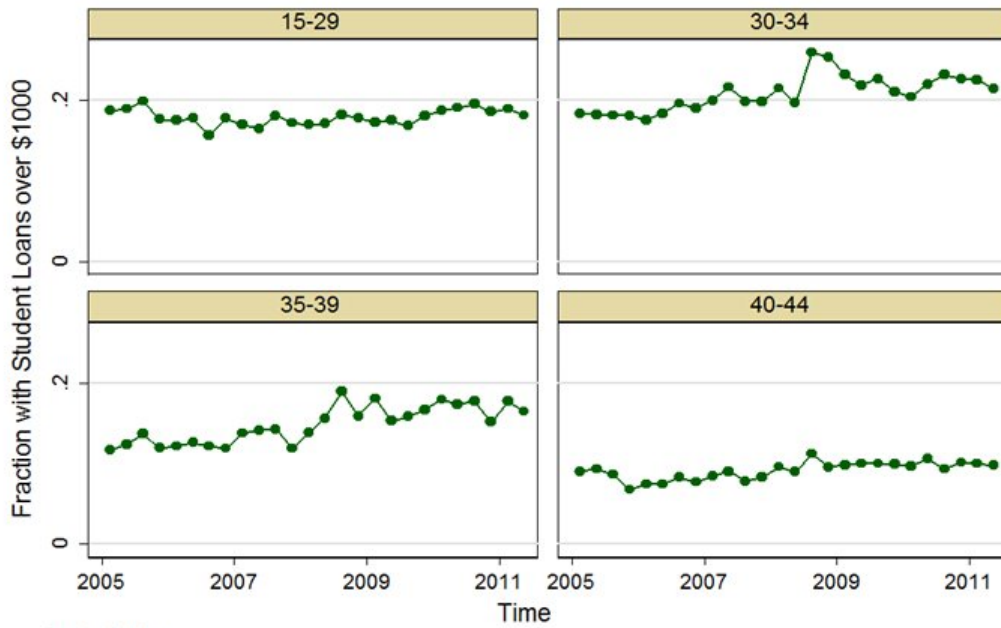


Figure 3.18: Fraction of Filers with Student Loan Debt



Graphs by Age



Table 3.27: Contribution from Home Ownership

Time Period	Filers w. Home Ownership or Mortgage Debt	Total Filers	Contribution (%)
07/2007-06/2008	14653	77122	
07/2008-06/2009	23909	99621	41
07/2009-06/2010	28282	104748	49
07/2010-06/2011	25456	93760	65

thirties with student debt did rise during the recession. However, this change was relatively small, as the fraction rose from just under 20% to just over 22%. This suggests that there was not a large change in the fraction of filers with a university degree during the recession.<sup>41</sup>

### 3.3.10 Changes in Filer Characteristics

We now examine how filer composition is related to provincial unemployment. Using the fact that unemployment predicts insolvency, we test whether average filer characteristics in each province vary with unemployment. In particular, we consider:

$$\text{Characteristic Growth Rate}_{t,p} = \text{Trend} + \Delta \text{Unemp. Rate}_{t,p} + \Delta \text{Unemp. Rate}_{t-1,p} + \epsilon_{t,p}$$

<sup>41</sup>Sullivan, Warren, and Westbrook [2000] document that many U.S. filers have some college education, although university graduates are less likely than non-degree holders to file for bankruptcy.

Table 3.28 reports the regression results. Again, there are several indications that filers are becoming more “middle-class.” Specifically as unemployment rises, individuals are more likely to own a home, live with someone – especially if they have kids. The initial filers are also more likely to be male and then female, which suggests they may earn more income. One might expect that proposals are more likely to be filed when higher unemployment results in more “middle-class” families experiencing debt problems. However, we cannot reject this story due to the impact of the September 2009 reforms that sought to make proposals more attractive.

Table 3.29 show how assets and capacity for loan repayment changes with unemployment. Although income does not change, total assets increase, the net worth and net worth-to-income ratio rise, while total liabilities and total unsecured liabilities rise. Overall, this supports the interpretation that the rise in filings during the recession was driven by more middle class filers.

Table 3.28: Unemployment and Provincial Filer Characteristics: 2007Q1-2011Q2

	(1) Age	(2) Cohabitation	(3) Cohabitation if kids	(4) Home Owner	(5) Proposal Fraction	(6) Male
Unemployment Rate Change	0.00188 (1.75)	0.00991 * (2.50)	0.0241 *** (5.83)	0.0204 * (2.20)	-0.00332 (-0.20)	0.00982 ** (3.21)
Unemployment Rate Change (t-1)	-0.000907 (-0.85)	-0.00674 (-1.70)		-0.000323 (-0.03)	-0.0456 ** (-2.74)	-0.00705 * (-2.30)
Reform					0.194 *** (4.20)	
Constant	0.00371 *** (3.83)	0.00736 * (2.05)	0.000382 (0.10)	0.0402 *** (4.81)	0.0290 (1.80)	-0.00348 (-1.26)
<i>N</i>	170	170	170	170	170	170
adj. <i>R</i> <sup>2</sup>	0.019	0.063	0.163	0.020	0.124	0.110

Note: Dependent variables expressed as growth rates of means. Reform is an indicator for second half of 2009 to capture increased proposal limits. *t* statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 3.29: Unemployment and Provincial Filer Characteristics: 2007Q1-2011Q2

	Filer Income	Total Assets	Net Worth to Income	Mean Net Worth	Total Liabilities	Total Uns. Liabilities
Unemployment Change	-0.0019 (-0.79)	0.0207* (2.23)	0.0158** (2.78)	0.0143** (2.66)	0.0173*** (3.47)	0.0115*** (3.66)
Unemployment Change (t-1)	-0.0017 (-0.72)	-0.0089 (-0.96)	0.0123* (2.16)	0.0110* (2.05)	0.00139 (0.28)	0.00509 (1.62)
Constant	0.00830 *** (3.91)	0.0566 *** (6.74)	-0.0018 (-0.34)	0.00962* (1.98)	0.0312 *** (6.93)	0.0120 *** (4.23)
<i>N</i>	170	170	170	170	170	170
adj. <i>R</i> <sup>2</sup>	-0.007	0.035	0.042	0.038	0.06	0.064

Note: Dependent variables expressed as growth rates of means. *t* statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

We examine whether the debt-level of filers changed during the recession, conditional on socio-demographic characteristics and current income and expenses (which are correlated with average income prior to filing). We restrict attention to individuals with housing assets of less \$10,000 to help control for any additional unobserved heterogeneity.

Table 3.30 shows filers appeared to have larger debt during and after the recession. In particular, debt levels (conditional on filer characteristics) initially increase and then decline. This suggests that filers were able to obtain more debt prior to the recession, but faced tighter lending standards after aggregate economic conditions deteriorated.

### **3.4 Conclusion**

The 2008-09 recession witnessed an almost 50% jump in personal insolvency filings in Canada. Our analysis suggests that while the sharp post-Lehman rise in unemployment was a key factor, the tightening of lending standards were also important. We also find that both of these channels play an important role in accounting for cyclical fluctuations in insolvency filings during previous business cycles.

Our analysis of the characteristics of filers documents significant changes in the characteristics of filers over 2007-2011. In particular, both the fraction of unemployed filers and the share of filers with “middle-class” characteristics increased during the 2008-09 recession. While this provides supportive evidence for the role of labour and credit market conditions in accounting for the

Table 3.30: Debt Levels for Individuals with Less than \$10,000 in Housing Assets

	(1) Total Debt	(2) Unsecured Debt	(3) Secured Debt
p2	2035.1*** (10.31)	1128.6*** (6.48)	906.7*** (9.33)
p3	2421.2*** (12.37)	1305.9*** (7.56)	1120.4*** (11.62)
p4	1316.6*** (6.55)	314.2 (1.77)	1007.2*** (10.18)
Age	1025.7*** (35.15)	1402.5*** (54.50)	-378.4*** (-26.34)
Age Squared	-9.766*** (-32.11)	-12.47*** (-46.50)	2.724*** (18.19)
Male	5282.7*** (37.55)	5350.9*** (43.12)	-77.76 (-1.12)
Cohabiting	1938.8*** (10.57)	1895.7*** (11.72)	43.26 (0.48)
Single Parent	976.6*** (3.82)	1724.7*** (7.66)	-748.1*** (-5.95)
Kids	293.8** (3.21)	-459.0*** (-5.69)	756.2*** (16.80)
Available Family Inc Assets	-0.0437 (-1.28) 0.942*** (980.48)	0.122*** (4.07) 0.0630*** (74.36)	-0.164*** (-9.82) 0.879*** (1857.84)
Housing Expense	8.556*** (46.67)	3.623*** (22.40)	4.940*** (54.72)
Insurance Expense	22.33*** (29.65)	27.70*** (41.72)	-5.328*** (-14.37)
Medical Expense	16.56*** (10.97)	25.89*** (19.45)	-9.333*** (-12.56)
Non Dis Expense	10.81*** (37.86)	11.69*** (46.45)	-0.976*** (-6.94)
Provincial Controls	Yes	Yes	Yes
<i>N</i>	374963	374963	374963
adj. <i>R</i> <sup>2</sup>	0.882	0.533	0.945

*t* statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

rise in insolvency, it also points to the need to better understand the distribution of household debt across households, and the vulnerability of households to economic shocks. This suggests that further work is needed to better understand the underlying causes of cyclical movements in insolvencies and consumer credit.

## 3.5 Bibliography

- AGARWAL, S., AND C. LIU (2003): "Determinants of Credit Card Delinquency and Bankruptcy: Macroeconomic Factors," *Journal of Economics and Finance*, 27(1), 75–84.
- ALLEN, J., AND E. DAMAR (2012): "Household Insolvency in Canada," *Bank of Canada Review*, 2011-12.
- BISHOP, P. (1998): "A Time Series Model of the U.S. Personal Bankruptcy Rate," Federal Insurance Deposit Corporation Bank Trends 98-01.
- BRIGHTON, J., AND J. CONNADIS (1982): *Consumer Bankrupts in Canada*. Consumer and Corporate Affairs Canada, Ottawa.
- DEN HAAN, WOUTER J., S. S., AND G. YAMASHIRO (2009): "Bank Loan Portfolios and the Canadian Monetary Transmission Mechanism," *Canadian Journal of Economics*, 42, 1150–1175.
- DERITIS, C., M. ACKCAY, AND S. KERNYTSKY (2012): "Cautious Optimism for Canadian Credit Cards," *Equifax Report*.
- DUNCAN, K. A., J. E. FAST, AND P. JOHNSON (2012): "Profiles of Canadian Households Undertaking Insolvency Procedures Pre and Post Recession," OSB Research Paper.
- FAY, S., E. HURST, AND M. J. WHITE (2002): "The Household Bankruptcy Decision," *American Economic Review*, 92(3), 706–718.
- GARRETT, T., AND H. WALL (2013): "Personal-Bankruptcy Cycles," *Macroeconomic Dynamics*, (1), 1–20.
- GROSS, D., AND N. SOULELES (2002): "An Empirical Analysis of Personal Bankruptcy and Delinquency," *The Review of Financial Studies*, 15(1), 319–347.

- LIVSHITS, I., J. MACGEE, AND M. TERTILT (2010): "Accounting for the Rise in Consumer Bankruptcies," *American Economic Journal: Macroeconomics*, 2, 165-193.
- LUCKETT, C. (2002): "Personal Bankruptcies," in *The Impact of Public Policy on Consumer Credit*, ed. by T. Durkin, and M. Staten, pp. 69-102. Kluwer Academic Publishers.
- MACGEE, J. (2012): "The Rise in Consumer Bankruptcy and Consumer Credit: Cause for Concern?," Commentary No. 356, C.D. Howe Institute.
- RAMSAY, I. (1999): "Individual Bankruptcy: Preliminary Findings of a Socio-Legal Analysis," *Osgoode Hall Law Journal*, 37(1), 16-82.
- RAVN, M. O., AND H. UHLIG (2002): "On adjusting the Hodrick-Prescott filter for the frequency of observations," *Review of Economics and Statistics*, 84(2), 371-375.
- SARRA, J. (2011): "At What Cost? Access to Credit in a Post-Financial Crisis Canada," Office of Superintendent of Bankruptcy, mimeo.
- SCHWARTZ, S. (1999): "The Empirical Dimension of Consumer Bankruptcy: Results from a Survey of Canadian Bankrupts," *Osgoode Hall Law Journal*, 37, 84-125.
- SERVICES, E. A. (2012): "Canadian Consumer Credit Trends," *Equifax Report*.
- SULLIVAN, T. A., E. WARREN, AND J. L. WESTBROOK (2000): *The Fragile Middle Class*. Yale University Press, New Haven and London.
- VISA USA (1996): "Consumer Bankruptcy: Causes and Implications," *VISA Consumer Bankruptcy Reports*.



## **Chapter 4**

# **Aggregate Fluctuations, Consumer Credit, and Bankruptcies**

### **4.1 Introduction**

Despite a large and growing literature that examines how default possibilities influence credit market outcomes and consumer welfare, little attention has been paid to how cyclical fluctuations in bankruptcies interact with lenders' credit granting decisions and households borrowing. This is surprising, as the recent recession saw both a rapid rise in consumer bankruptcies, and broad concern about the potential implications of high consumer debt levels for aggregate consumption.

We address this gap in two ways. First, we document the historical cyclical relationships between different measures of U.S. consumer credit market

behavior – delinquencies, charge-offs, bankruptcies, interest rates – and consumption. Second, we construct, and analyze a quantitative model of consumer borrowing and bankruptcy where agents' idiosyncratic income shocks and financial intermediation costs are affected by aggregate shocks. We use the model to decompose the driving forces behind cyclical fluctuations in the consumer credit market and their impact on defaults. In particular, we seek to identify the impact of changes in the composition of borrower risk on average interest rate and borrowing.

Our empirical analysis documents that fluctuations in consumer bankruptcies and charge-offs are large and counter-cyclical. Our proxy for the borrowing interest faced by consumers, the average (real) credit card interest rate, is counter-cyclical for 1973-2012 period, but exhibits a small positive correlation with GDP since 1993. Importantly, unsecured consumer borrowing is pro-cyclical, although measures such as revolving credit (primarily credit card debt) exhibit countercyclical fluctuations during the Great Moderation (1993-2006).

Our quantitative approach extends a standard small-open economy incomplete market model with bankruptcy to incorporate aggregate shocks. This framework allows for borrowing constraints to move endogenously with income risk, and thus can potentially produce pro-cyclical debt without intermediation

shocks. However, for reasonable parameter values, we find that aggregate fluctuations in income generates counter-cyclical debt despite matching the cyclicity of filings and consumption in the data. In addition to missing on the cyclicity of debt, the benchmark model implies cyclical volatilities in filing, interest rates and debt well below the data.

We find that introducing “intermediation shocks” – exogenous counter-cyclical shocks to the cost of funds for lenders – moves the model predictions closer to the data.<sup>1</sup> One common explanation for increased costs to financial institutions is increased scrutiny [Weinberg, 1995]. Recently, Corbae and DErasmo [2013] documents that both consumer loan rates and markups are counter-cyclical. Adding “intermediation shocks” to the model, generates pro-cyclical debt, and the volatility of filings and interest rates rise closer to the data. This suggests that counter-cyclical intermediation shocks may play an important role in consumer credit markets.

The model is a heterogenous agent life-cycle model with incomplete markets, which builds upon Livshits, MacGee, and Tertilt [2007].<sup>2</sup> Each period, households face idiosyncratic uncertainty regarding their income and expenses.

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<sup>1</sup>Recently, Jermann and Quadrini [2012] argue that real and financial variables are affected by “financial shocks,” which affect one’s ability to raise capital. They find these shocks to be counter-cyclical.

<sup>2</sup>This environment builds on the competitive theory of equilibrium default pioneered by Eaton and Gersovitz [1981] and adapted to analyze consumer bankruptcy by Chatterjee, Corbae, Nakajima, and Ríos-Rull [2007] and Livshits, MacGee, and Tertilt [2007].

Aggregate shocks impact the probability of income shocks, as well as the risk-free rate of interest. After the realization of the aggregate state (and the individual shocks), households decide whether or not to file for bankruptcy, given some bankruptcy rules. If bankruptcy is not declared, households can borrow (and save) via one-period non-contingent bonds with perfectly competitive financial intermediaries. When making loans, financial intermediaries can observe each household's earnings process, age, current asset holdings and aggregate state. Therefore, in equilibrium, bond prices vary with income, age, total borrowing of the debtor and aggregate state.

Closest in focus to our work are Nakajima and Ríos-Rull [2005] and Gordon [2013]. Nakajima and Ríos-Rull [2005] introduce aggregate fluctuations into the Chatterjee, Corbae, Nakajima, and Ríos-Rull [2007] framework. One limitation of their approach is that they assume that all shocks are realized (known) before households make borrowing decisions. As a result, all of aggregate fluctuations are fully priced into the ex ante lending schedule faced by borrowers. In contrast, under our timing, lenders set interest rates before the aggregate state is realized. Our model predicts counter-cyclical fluctuations in bankruptcy, whereas their literature predicts the opposite.<sup>3</sup> Gordon [2013] also extends the Livshits, MacGee, and Tertilt [2007] to include aggregate shocks. Unlike our paper, he focuses on how aggregate income risk impacts the welfare gains from alternative bankruptcy regimes, whereas we focus on the extent to

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<sup>3</sup>The handbook of macro (Chapter 2) summarizes work on the impact of contractionary monetary shocks on consumer borrowing.

which the model can match key cyclical patterns observed in the data.

Motivated by empirical studies on the cyclical variability of consumption and the relationship between consumer borrowing and aggregate consumption, several papers have sought to quantify the impact of exogenous shocks to borrowing constraints.<sup>4</sup> Ludvigson [1999] finds that introducing exogenous variations in borrowing constraints in a model with infinitely lived consumers helps the model to more closely match cyclical fluctuations in aggregate consumption. Krusell and Smith [1998] match the secular and cyclical properties of U.S. consumption and borrowing using a model economy with a mix of patient (standard) and impatient (borrowing constrained) households. Unlike Krusell and Smith [1998], the model abstracts from capital accumulation, and there is no trend growth in income.

There is empirical evidence that unsecured credit markets are impacted by shocks to household incomes. Sullivan [2008] uses quarterly data from the SIPP that tracks household unsecured borrowing from April 1996 to March 2000 (1996 Panel) and February 2001 to January 2004 (2001 Panel). He finds that while the lowest income households (bottom decile of income), do not use unsecured credit to smooth earnings loss, those in the second and third deciles do – with a point estimate of 11.5 to 13.4 cents per dollar of earnings lost due

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<sup>4</sup>Bacchetta and Gerlach [1997] use the degree of excess sensitivity of aggregate consumption as a proxy for credit constraints. They examine data from the U.S., Canada, U.K., Japan and France from 1970-1995 for consumption, disposable income and mortgage credit. Bacchetta and Gerlach [1997] extend the excess sensitivity and liquidity constraints literature by explicitly adding credit variables (real mortgage credit and real consumer credit) and lending rate spreads (borrowing/lending) to the regression analysis.

to unemployment, while highest earning households run down savings in response to unemployment.<sup>5</sup> Using data provided by a major credit card lender, Agarwal and Liu [2003] find that variations in county level unemployment rates help account for delinquency rates on credit cards between January 1994 and December 2001.

The remainder of the paper is organized as follows. We summarize background information on consumer bankruptcy in Section 2, and key cyclical properties of consumer credit markets in Section 4.3. The basic environment for evaluating the predictions of the standard model is presented in Section 4.4. Section 5 presents our results, and the final section offers a brief conclusion.

## **4.2 Consumer Bankruptcy in the U.S.**

American households can choose between two bankruptcy procedures: Chapter 7 and Chapter 13.<sup>6</sup> Under Chapter 7, all unsecured debt is discharged in exchange for non-collateralized assets above an exemption level, and debtors are not obliged to use future income to repay debts.<sup>7</sup> Chapter 13 permits debtors to keep their assets in exchange for a promise to repay part of their debt over

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<sup>5</sup>Hurst and Stafford (2004) look at the use of home equity to smooth consumption for households with low levels of liquid assets. They find that this is used by households to smooth consumption.

<sup>6</sup>See Mecham [2004] for a detailed description of consumer bankruptcy law in the United States.

<sup>7</sup>The 2005 bankruptcy reform requires households with income above a threshold to enter into a payment plan. (See White [2007] for details on the 2005 reforms.)

the ensuing 3 to 5 years.<sup>8</sup>

Most bankrupts file under Chapter 7 (approximately 70 percent), which is the focus of our paper. Debtors who file under Chapter 7 are not permitted to refile under Chapter 7 for six years, although they may file under Chapter 13. Filers must pay the bankruptcy court filing fee of \$200 and fees for legal advice that typically range from \$750 to \$1,500 (Sullivan, Warren, and Westbrook [2000]). In addition, a debtor filing for bankruptcy has to submit a detailed list of all creditors, amounts owed, all assets, monthly living expenses as well as the source and amount of income. A typical Chapter 7 bankruptcy takes about 4 months from start to completion.

Despite the dramatic secular increase in bankruptcy filings, the typical bankrupt today is remarkably similar to the typical bankrupt of twenty years ago (Sullivan, Warren, and Westbrook [2000], Warren [2002]). A typical bankrupt is lower middle-class (with income roughly 30-50% lower than that of the average household), in their thirties with an extremely high debt-to-income ratio and more unsecured debt, especially credit card debt, than the median household.

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<sup>8</sup>Legal actions by creditors and most garnishments are halted upon filing for bankruptcy, including phone calls and letters from creditors seeking repayment.

### 4.3 Cyclical Patterns of Credit, Consumption and Defaults

We examine annual data on consumer debt, consumption and bankruptcies from 1973-2012.<sup>9</sup> We detrend each series with a Hodrick and Prescott [1997] filter, and report the relationships between the cyclical deviations from trend. We set the smoothing parameter to 6.25 as argued to be appropriate for annual data by Ravn and Uhlig [2002].<sup>10</sup> We analyze logged data, so that deviation from trend approximate percentage differences. Given our interest in bankruptcy, we focus on the unsecured consumer credit.

Table 4.3 reports the correlations between measures of credit market variables and consumption. Given the substantial rise in consumer debt since the 1970s, as well as the development and growth of products such as credit cards and home equity lending, we compute correlations for the 1973-2012 period as well as before (i.e., 1973-1992) the Great Moderation (which we identify as 1993 to 2006) and after (i.e., the Great Recession).

There are several key relationships worth noting. First, bankruptcy filings are counter-cyclical (see Table 4.3 and the Figure 4.3). Cyclical fluctuations in credit discharge rates are similar to bankruptcy filings, which is not surprising as the discharge of debt via bankruptcy filings accounts for a large share

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<sup>9</sup>The data we use is reported in the Appendix in Table C.1.

<sup>10</sup>Using growth rates instead of filtering the data produces quantitatively similar results.



of credit card discharges. As a proxy for the borrowing interest faced by consumers, we use the average (real) on credit cards.<sup>11</sup> While credit card rates are counter-cyclical for the 1973-2012 period, they have a small positive correlation with GDP since 1993.

Consumer debt tends to be procyclical, although some debt measures shifts are countercyclical over 1993-2006. The narrowest measure of consumer credit we examine is revolving credit, which primarily consists of outstanding credit card balances. This is pro-cyclical, with the exception of the 1993-2006 period when it is counter-cyclical. A practical question – which also arises in mapping the model to the data – is how to account for charge-offs when measuring the cyclicity of debt. When we adjust the stock of revolving credit using the credit card charge-off rate over 1985-2012, we find that the correlation between revolving credit and GDP changes from -0.05 to -0.34.<sup>12</sup>

We consider several other proxies for unsecured consumer credit. The Federal Reserve Consumer Credit Report (G.19 Release) includes both revolving and non-revolving credit, where the later includes auto loans as well as consumer installment loans. This debt measure is procyclical, with the exception of the “great moderation.” One concern is that this shift in cyclical patterns may reflect the growth of home equity lines of credit, which has become a substitute for traditional consumer lending. This leads us to add home equity lending (which is available since 1990) to consumer credit. The correlation of this debt

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<sup>11</sup>The rate is the unweighed average credit card rate on all balances less inflation.

<sup>12</sup>The published charge-off series we use begins in 1985.

Table 4.1: Correlations with GDP<sup>1</sup>

	73-92	93-06	07-12	73-12
Filings/HH	-0.61	-0.44 <sup>2</sup>	-0.90	-0.46
Charge-Offs <sup>3</sup>	-0.91	-0.55	-0.87	-0.74
Consumption	0.89	0.88	0.98	0.91
Consumer Credit	0.82	-0.20	0.42	0.63
Revolving Credit	0.64	-0.24	-0.03	0.51
Consumer Debt + Home Equity Loans	0.68	-0.09	0.96	0.62
Cons. Credit/Disposable Income	0.68	-0.33	0.06	0.43
Credit Card Interest Rates	-0.72	0.06	0.15	-0.59
Disposable Income	0.84	0.52	0.97	0.81

Notes. 1. Annual data detrended with an HP-filter. 2. Excludes 05 and 06. 85 Onwards.

measure with GDP declines to -0.09 from -0.20 over 1993-2006, and becomes more strongly procyclical for the 2007-12 period..

Since the carrying cost of consumer debt needs to be evaluated relative to disposable income, we consider whether normalizing consumer credit by disposable income changes the cyclicity. However, this has a relatively small impact on the correlations.

We also examine quarterly correlations. Specifically, we compute the correlations between GDP along with its leads and lags. Overall, we see similar patterns as in Table 4.3. However, lagged consumer credit is weakly counter-cyclical while the lead of consumer debt to income is pro-cyclical. Real credit card interest rates counter-cyclically lead GDP.

Table 4.3 displays the volatilities of the credit market variables, debt and

Table 4.2: Quarterly Correlations with GDP

	Y(-2)	Y(0)	Y(2)
Filings/HH	-0.44	-0.45	-0.25
Charge Offs	-0.65	-0.74	-0.57
Real Consumption	0.74	0.92	0.71
Consumer Credit	-0.42	0.17	-0.04
Revolving Consumer Credit	0.39	0.02	-0.29
Debt/Inc	0.14	-0.07	-0.14
Real Credit Card Interest Rates	0.10	-0.08	-0.36

Table 4.3: Volatility Relative to GDP:  $\frac{\sigma}{\sigma_y}$ <sup>1</sup>

	73-92	93-06	07-12	73-12
Filings/HH	5.9	11.9 <sup>2</sup>	8.5	11.7
Charge-Offs <sup>3</sup>	9.9	16.9	17.2	15.6
Consumption	0.8	0.8	0.8	0.8
Consumer Debt	2.6	2.9	1.8	2.5
Revolving Credit	6.4	3.2	2.1	5.6
Consumer Debt + Home Equity Loans	2.6	2.2	1.3	2.6
Consumer Credit/Disposable Income	2.2	3.1	1.7	2.2
Credit Card Interest Rates	12.5	7.0	5.2	11.1
Disposable Income	1.2	1.2	1.4	1.2

Notes. 1. Annual data detrended with an HP-filter. 2. Excludes 05 and 06. 85 Onwards.

consumption relative to GDP. As Figure 4.3 immediately shows, filings are extremely volatile as they differ by more than a factor of 10. Similarly, charge-offs and real credit card interest rates are very volatile relative to GDP. For the most part, there are no trends in volatility. The exceptions are debt and real credit card interest rates, which appears to have become less volatile over time.

Figure 4.1: GDP and Insolvency Filings

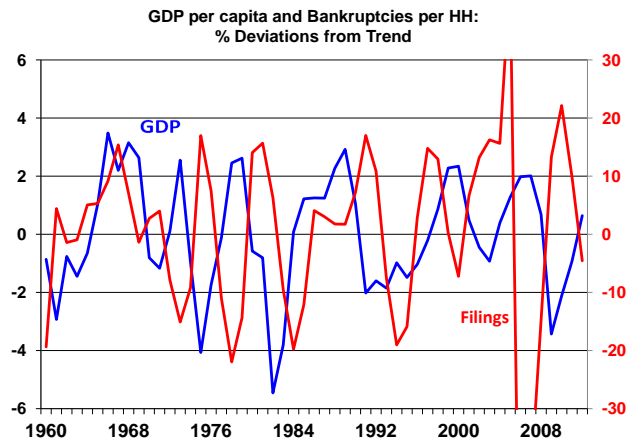
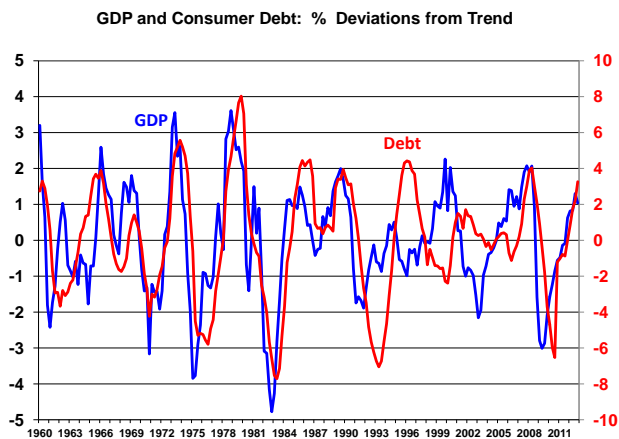


Figure 4.2: GDP and Total Consumer Credit



## 4.4 Environment

In this section, we outline the model, and describe our benchmark parametrization which serves as a starting point for the numerical experiments.

### 4.4.1 The Model

We extend the “Fresh Start” model of consumer bankruptcy of Livshits, MacGee, and Tertilt [2007] by incorporating an earning process and lending cost (interest rate) which vary with the aggregate state. These extensions allow us to evaluate the contributions of these two aggregate risk channels to cyclical fluctuations in unsecured consumer borrowing and bankruptcies.

The model economy is populated by overlapping generations of  $J$ -period lived households. Each generation is comprised of measure 1 of households facing idiosyncratic and aggregate uncertainty. Markets are incomplete, with agents borrowing using non-contingent person-specific one-period bonds and saving at an exogenously given interest rate.<sup>13</sup> Households have the option to declare bankruptcy.

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<sup>13</sup>As this paper focuses on the market for unsecured debt (which comprises a small fraction of total borrowing in the United States), significant feedback effects on the aggregate risk-free interest rate seem unlikely. Given the significant computational burden associated with closing the model, we assume that the aggregate capital market takes the form of a small open economy.

## Households

Households maximize expected discounted life-time utility from consumption:

$$E \sum_{j=1}^J \beta^{j-1} u \left( \frac{c_j}{n_j} \right), \quad (4.1)$$

where  $\beta$  is the discount factor,  $c_j$  is household consumption and  $n_j$  is the size of a household of age  $j$  in equivalence scale units.

The labor income of a household  $i$  of age  $j$  is the product of an age-dependent labor endowment and productivity shocks:

$$y_j^i = \bar{e}_j z_j^i \eta_j^i, \quad (4.2)$$

where  $\bar{e}_j$  is the deterministic endowment of efficiency units of labor,  $z_j^i$  is a persistent shock to the household's earnings, and  $\eta_j^i$  a transitory shock.

The probabilities of the persistent income shocks vary with the realization of the aggregate state  $\omega$ . The aggregate shock impacts the distribution of idiosyncratic shocks in the current period, and thus, shifts the riskiness of income the following period when the aggregate state is persistent.

Besides the persistent and transitory income shocks, households face another form of idiosyncratic uncertainty: they are subject to possible expense shocks  $\kappa \geq 0$ . An expense shock directly changes the net asset position of a household. Expense shocks are independently and identically distributed, and are independent of income shocks (and hence do not vary with the aggregate shocks). We assume that the set of possible expense shocks  $K$  is finite. The probability of shock  $\kappa_i$  is denoted by  $\pi_i$ .

A household can file for bankruptcy. As in Chapter 7, upon filing all debts are discharged, and the household enters the following period with a balance of zero (unless hit by an expense shock that period).<sup>14</sup> Filers also face several types of “punishment” which proxy for specific features of Chapter 7. First, bankruptcy cannot be declared two periods in a row. Second, to capture the requirement that borrowers make a good faith effort to repay their debt, we force bankrupt households to repay a fraction  $\gamma$  of their earnings during the period in which they file.<sup>15</sup> Since we lack a direct measure of these implicit constraints on bankruptcy, we calibrate this bankruptcy cost parameter so as to match the debt facts.

The timing is as follows. At the beginning of the period, each household realizes its productivity and expense shocks. If the household receives an expense shock, then the debt of the household is increased (or savings decreased) by the amount of the shock. The household then decides whether to file for bankruptcy or not. If bankruptcy is declared, creditors garnish labor income

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<sup>14</sup>This means that bankrupts cannot save or borrow during the default period because all assets are seized during a Chapter 7 bankruptcy. Given our period length of three years, one might wonder if the restriction to not allow savings constitutes a significant punishment. It turns out that the no-savings constraint is binding only for a very small fraction of households and that results do not change significantly when this assumption is relaxed.

<sup>15</sup>The U.S. bankruptcy code specifies that borrowers must act in “good faith”, so that someone who borrows and immediately files for bankruptcy risks having their petition denied. Prior to 1984, courts had the implicit right to dismiss a case based on “bad faith” behavior by the debtor. The Bankruptcy Amendments and Federal Judgeship act of 1984 and the 1986 amendments to section 707(b) of the Code formalized this by explicitly allowing bankruptcy trustees to make a motion for dismissal for substantial abuse. While the interpretation of “substantial abuse” has varied across courts, the ability to repay a significant fraction of one’s debt has often played a large role in courts’ decisions to dismiss debtors’ bankruptcy petitions (see Cain [1997] and Wells, Kurtz, and Calhoun [1991]).

and the consumer is allowed to spend the remaining income. Filers are not allowed to save or borrow, thus, they consume all earnings net of debt-recovery  $\gamma$  (and “burning”). Households who do not declare bankruptcy decide on their asset holdings for the following period and their current consumption.

### **Financial Intermediaries**

Financial markets are perfectly competitive. Intermediaries accept deposits from savers and make loans to borrowers. The risk-free savings rate  $r^s(\omega)$  is given exogenously, and varies with the aggregate state. Loans take the form of one period non-contingent bond contracts. However, the bankruptcy option introduces a partial contingency by allowing filers to discharge their debts. The face value of a loan to be repaid next period is denoted by  $d'$ . Savings are denoted by  $d' < 0$ . Intermediaries incur a proportional transaction cost of making loans,  $\tau$ .

Intermediaries have complete information about borrowers: They observe the total level of borrowing  $d'$ , the current persistent productivity shock  $z$ , the aggregate state  $\omega$  and the borrower’s age  $j$ .<sup>16</sup> This allows intermediaries to accurately forecast the default probability of a borrower,  $\theta(d', z, \omega, j)$ , and price the loan accordingly.

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<sup>16</sup>The realizations of the transitory shock  $\eta$  and the expense shock  $\kappa$  do not contain any additional information on the default risk.



## Equilibrium

In equilibrium, perfect competition and complete information imply that intermediaries make zero expected profit on each loan and that cross subsidization of interest rates across different types of borrowers does not occur. Therefore the individual bond price is determined by the default probability of the issuer and the risk-free bond price. Without debt-recovery, without usury law and with full discharge of debt, the zero profit condition is  $q^b(d', z, j, \omega) = (1 - \theta(d', z, \omega, j))\bar{q}^b(\omega)$ , where  $\bar{q}^b \left( = \frac{1}{1+r^s(\omega)+\tau} \right)$  is the price of a bond with zero default probability.

For positive levels of debt-recovery, this formula needs to be adjusted. The *unrestricted bond price under debt recovery* is

$$q^{ub}(d', z, \omega, j) = (1 - \theta(d', z, \omega, j))\bar{q}^b(\omega) + \theta(d', z, \omega, j)E \left( \frac{\gamma y}{d' + \kappa'} \right) \bar{q}^b(\omega) \quad (4.3)$$

where  $E \left( \frac{\gamma y}{d' + \kappa'} \right)$  is the expected rate of recovery, assuming that when a household defaults, the amount recovered is allocated proportionately to expense debt and personal loans.

Lastly, taking into account the interest rate ceiling  $\bar{r}$ , the *equilibrium bond price* is

$$q^b(d', z, \omega, j) = \begin{cases} q^{ub}(d', z, \omega, j) & \text{if } q^{ub}(d', z, \omega, j) \geq \frac{1}{1+\bar{r}} \\ 0 & \text{otherwise} \end{cases} \quad (4.4)$$

Households take the bond price schedule as given when making decisions. The problem of a household is defined recursively using three distinct value

functions.  $V$  is the value of a “normal period,” while  $\bar{V}$  is the value of declaring bankruptcy. Although bankruptcy cannot be declared two periods in a row, households have the option to default when they are ineligible for bankruptcy.<sup>17</sup> If a household chooses this option, they face the same proportional costs as if they were able to file for bankruptcy. However, unlike in bankruptcy, no debt is discharged. Given that households in default no longer are borrowing from the market, we assume their debt is rolled over at a fixed interest rate  $r^r$ . Note that the only debt such a household holds is debt arising from an expense shock. After the forced repayments and applying interest rate  $r^r$ , next period’s debt for this case is equal to  $(\kappa - \gamma \bar{e}_j z \eta)(1 + r^r)$ . The value function for a household defaulting in the period following bankruptcy is denoted by  $W$ . The value functions are given by:

$$V_j(d, z, \omega, \eta, \kappa) = \max_{c, d'} \left[ u \left( \frac{c}{n_j} \right) + \beta E \max \{ V_{j+1}(d', z', \omega', \eta', \kappa'), \bar{V}_{j+1}(z', \omega', \eta') \} \right]$$

$$\text{s.t. } c + d + \kappa \leq \bar{e}_j z \eta + q^b(d', z, \omega, j) d'$$
(4.5)

$$\bar{V}_j(z, \omega, \eta) = u \left( \frac{c}{n_j} \right) + \beta E \max \{ V_{j+1}(0, z', \omega', \eta', \kappa'), W_{j+1}(z', \omega', \eta', \kappa') \}$$

$$\text{s.t. } c = (1 - \lambda)(1 - \gamma)(\bar{e}_j z \eta - \phi)$$
(4.6)

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<sup>17</sup>We need to introduce this option to deal with the possibility that a household may not be able to repay the realized value of an expense shock in the period immediately following bankruptcy. In practice, this is not of much importance in the model since this situation rarely arises.

$$\begin{aligned}
W_j(z, \omega, \eta, \kappa) &= u\left(\frac{c}{n_j}\right) + \beta E \max \{V_{j+1}(d', z', \omega', \eta', \kappa'), \bar{V}_{j+1}(z', \omega', \eta')\} \\
\text{s.t. } c &= (1 - \lambda)(1 - \gamma)\bar{e}_j z \eta, \quad d' = (\kappa - \gamma\bar{e}_j z \eta)(1 + r^r)
\end{aligned} \tag{4.7}$$

An equilibrium is a set of value functions, optimal decision rules for the consumer, default probabilities, and bond prices, such that equations (4.5)-(4.7) are satisfied, and the bond prices are determined by the zero profit condition, taking the default probabilities as given. The model can be solved numerically by backwards induction.

#### 4.4.2 Benchmark Calibration

Our approach is to choose parameters to match the US economy during the nineties, and then modify the income process and interest rates to match cyclical movements. Our discussion of how we choose long-run parameters is brief since we largely follow Livshits, MacGee, and Tertilt [2010].

##### Long-Run Averages

The non-cyclical parameterization consists of household and financial parameters. We summarize this parameterization in Table 4.4.

**Household Parameters** Households are born into the economy at age 20 and die at age 74. During the first 45 periods (ages 20-65) households receive

Table 4.4: Non-Cyclical Parameterization

Parameter	Target/Source
Periods (J)	45 Working Years + Retirement
Utility	$\frac{1}{1-\sigma}[c^{1-\sigma} - 1]$
Risk-aversion ( $\sigma$ )	2
Savings interest rate	Municipal Bonds
Age-profile of Earnings	Gourinchas and Parker '02
AR(1) Income Process	Storesletten, Telmer and Yaron '04
Expense Shocks ( $\eta$ )	Livshits, MacGee and Tertilt '07 Medical bills (MEPS 1996-97) Divorce (US Vital Stats, Equiv. Scale) Unwanted children (US Vital Stats, USDA)
Discount Factor ( $\beta$ )	0.83% Chapter 7 filings
Transaction cost ( $\tau$ )	12.4% Average borrowing int. rate
Garnishment ( $\gamma$ )	9% Unsecured Debt/Income ratio 4.8% Charge-off Rate

a stochastic endowment, while the final period corresponds to a nine year retirement in which households do not face any uncertainty. The period utility function is  $u(c) = \frac{c^{1-\sigma}-1}{1-\sigma}$ . We set the annual discount factor equal to 0.92 and the degree of risk aversion  $\sigma$  equal to 2.<sup>18</sup> Household size measured in equivalence units is taken from Livshits, MacGee, and Tertilt [2007].

The expense shocks are calibrated using data on expenses that are both unexpected and frequently cited by bankrupts as the cause of their bankruptcy. We consider three different sources of shocks: medical bills, divorces, and unplanned pregnancies. In our experiments, the expense shocks can take on three values:  $\kappa \in \{0, \kappa_1, \kappa_2\}$ . To calibrate the medical expense shock, we use data from

<sup>18</sup>We have also investigated somewhat higher and lower degrees of risk aversion ( $\sigma = 1.5$  and 2.5) and found that our results are robust to this modification.

the 1996 and 1997 Medical Expenditure Panel Survey (MEPS) and from the US Health Care Financing Administration (HCFA). MEPS provides detailed data on out-of-pocket medical expenses in 1996 and 1997 for a random sample of 7,435 households. We combine our estimate of these medical expenses with estimates of the cost of divorces and of an unplanned or unwanted child. Our calculations generate one shock that is 26.4 percent of (one model period) average income in the economy. The other shock is equal to 82.18 average income in the economy. The probabilities of being hit by these shocks are 7.1 percent and 0.46 percent, respectively (newly born and retired households are not subject to expense shocks).

The life-cycle profile of labor income is based on Gourinchas and Parker (2002). To incorporate aggregate fluctuations in the stochastic income process we modify an AR(1) income process used to calibrate the steady-state model. A large literature has estimated the volatility of log earnings using the following structure:  $\log y^i = z^i + \eta^i + g(X^i)$ , where  $g(X)$  captures the deterministic component of earnings, and  $z$  and  $\eta \sim N(0, \sigma_\eta^2)$  are respectively persistent and transitory random components. The log of the persistent idiosyncratic shock follows an AR(1) process,  $z_j^i = \rho z_{j-1}^i + \epsilon_j^i$ , where  $\epsilon_j^i \sim N(0, \sigma_\epsilon^2)$ . We set the benchmark value of  $\rho = 0.95$ ,  $\sigma_\epsilon^2 = 0.025$  and  $\sigma_\eta^2 = 0.05$ . These values are within the range of values reported by Storesletten, Telmer, and Yaron [2004], Hubbard, Skinner, and Zeldes [1994], and Carroll and Samwick [1997]. To feed these values into our model for the steady-state calibration, we discretize the

idiosyncratic income shocks using the Tauchen method outlined in Adda and Cooper [2003]. The persistent shock is discretized as a five state Markov process, and the initial realizations for newly-born households are drawn from the stationary distribution. When discretizing the transitory shock, we assume that 10% of the population receives a positive (negative) transitory shock each period, and choose the value of the support to match the variance.

We assume that the (exogenous) income of a retired household is the sum of two parts: an autonomous income of 20% of average earnings in the economy and an additional income of 35% of their own persistent earnings realization in the period before retirement. This leads to a progressive retirement income system with an average replacement rate of 55%, which is within the range of numbers reported in Butrica, Iams, and Smith [2004]. Note that total retirement income is higher as households also have private savings.

**Financial Market Parameters** The savings interest rate is set equal to 3.44%, as in Gourinchas and Parker [2002]. The rollover interest rate  $r^r$  is set to 20% annual. The three remaining parameters — the debt recovery rate  $\gamma$ , transaction cost  $\tau$ , and the interest rate ceiling  $\bar{r}$  — are chosen to match the facts from Table 4.4. This leads to a transactions cost of making loans of 3.50% annually. Together with the risk-free savings rate of 3.44%, the annual risk-free lending rate is 5.94%. The interest rate ceiling is set to a (high) value of 75% annually.<sup>19</sup>

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<sup>19</sup>As discussed in Livshits, MacGee, and Tertilt [2010], the failure to impose an interest rate ceiling leads to artificially high average interest rates.

The  $\gamma$  implied by this calibration is 0.5. It is worth emphasizing that this parameter captures many features of the default option introduced by bankruptcy, and that we do not interpret  $\gamma$  as mapping directly into what is recovered by lenders *after* a borrower has defaulted. Instead, this is intended to capture the fact that borrowers typically make a sequence of payments on unsecured debt before defaulting. As discussed in Livshits, MacGee, and Tertilt [2010], there is no direct empirical counter to determine if our parameter is too high (or low).

### 4.4.3 Cyclical Income Process

To incorporate aggregate fluctuations in the income process, we keep the income support fixed from the steady state calibration, and vary the persistent transition matrix with the aggregate state. We choose to model the aggregate shock process as a two state process, where the economy spends roughly 75% of the time in expansions and the probability of remaining in a recession (“bad” aggregate state) is one-third. Then, the transition probabilities (good,bad) in the good state are  $[7/9, 2/9]$ , and  $[2/3, 1/3]$  in the bad state.

We choose two transition matrices which imply that aggregate income falls by 3% during bad times, and rise by 1% during expansions, relative to the steady-state income process. We pick a single parameter which increases the probability of receiving a lower-level income level compared to the transition matrix from Section 4.4.2. Specifically, we use the  $\lambda$  such that a transition

matrix

$$\begin{pmatrix} \left(\frac{1-\lambda \sum_{j=2}^5 z_{1,j}}{\sum_{j=2}^5 z_{1,j}}\right) z_{1,1} & \lambda z_{1,2} & \lambda z_{1,3} & \cdots & \lambda z_{1,5} \\ \left(\frac{1-\lambda \sum_{j=2}^5 z_{2,j}}{\sum_{j=2}^5 z_{2,j}}\right) z_{2,1} & \lambda z_{2,2} & \lambda z_{2,3} & \cdots & \lambda z_{2,5} \\ \left(\frac{1-\lambda \sum_{j=3}^5 z_{3,j}}{\sum_{j=3}^5 z_{3,j}}\right) z_{3,1} & \left(\frac{1-\lambda \sum_{j=3}^5 z_{3,j}}{\sum_{j=3}^5 z_{3,j}}\right) z_{3,2} & \lambda z_{3,3} & \cdots & \lambda z_{3,5} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \left(\frac{1-\lambda z_{5,5}}{z_{5,5}}\right) z_{5,1} & \left(\frac{1-\lambda z_{5,5}}{z_{5,5}}\right) z_{5,2} & \cdots & \left(\frac{1-\lambda z_{5,5}}{z_{5,5}}\right) z_{5,4} & \lambda z_{5,5} \end{pmatrix}$$

matches the change in the aggregate level relative to steady state distribution.

The initial realizations for newly born households are drawn from the stationary distribution. During a recession, individuals receive less income at the beginning of their life. We choose  $\lambda'$  such that the first-period distribution is such that

$$D = \left[ \frac{1}{5} + \frac{\lambda'}{5}, \frac{1}{5} - \frac{\lambda'}{5^2}, \dots, \frac{1}{5} - \frac{\lambda'}{5^2}, \frac{1}{5} - \frac{2\lambda'}{5^2} \right]$$

there is a 3% drop in income during the first-period of their life and a 1% increase during expansions.

#### 4.4.4 Quantitative Experiments

We use the calibrated model to assess the importance of the two aspects of aggregate shocks — changes in distribution of income shocks, and shocks to financial intermediation — for the cyclical behaviour of consumer debt and bankruptcies; and to assess whether the standard model is capable of replicating the stylized facts. Table 4.5 reports the results from our quantitative experiments.



In our first experiment, we model the aggregate state as affecting only the income process, and not the cost of funds. We find that changes in income shocks alone cannot generate the volatilities we see in the data and miss the cyclical nature of consumer debt. Introducing intermediation shocks in the second experiment helps address both of these shortcomings, at least qualitatively. The model still struggles to match the volatilities observed in the data.

### **Experiment 1 - Income Shocks**

We first analyze the quantitative impact of income shocks in our benchmark economy. While our benchmark replicates several key empirical observations, income shocks alone fail to generate the cyclical nature of filing and consumption observed in the data. The implied volatility of bankruptcies (and thus, interest rates) are also well below those observed in the data.

A further issue is that aggregate income risk leads to countercyclical – not procyclical – debt. In response to a rise in transitory (negative) income shocks, households increase their borrowing to smooth consumption. This leads to a rise in aggregate debt during “recessions” in the model, driven primarily by an extensive margin, as more households borrow as a result of negative income shocks.

Why does this environment fail to generate large cyclical swings in bankruptcy filings? A key factor is that over the cycle the borrowing constraints do not really tighten during the recession in this model. In Figure 4.3, we plot

Table 4.5: Experiments

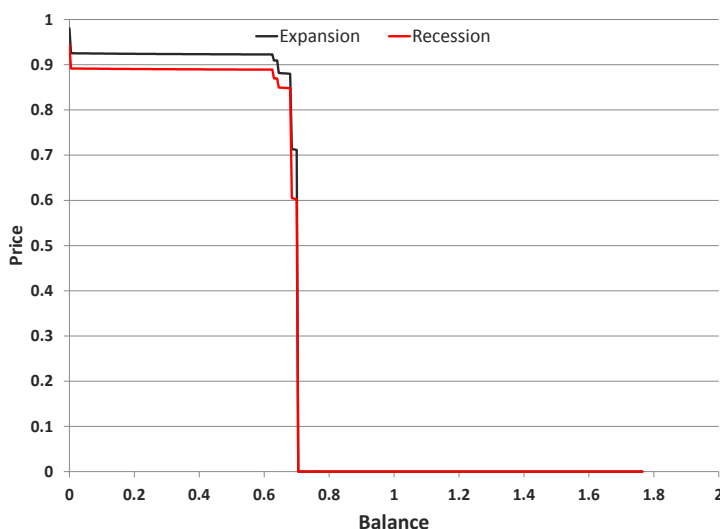
Series	Data		Constant Interest		Counter-Cyclical Int	
	$\sigma$	$\rho(\cdot, Y)$	$\sigma$	$\rho(\cdot, Y)$	$\sigma$	$\rho(\cdot, Y)$
GDP	1.98	1	1.87	1	1.78	1
Consumption	1.78	0.87	1.16	0.99	1.55	0.78
Filings	19.2	-0.40	0.77	-0.69	1.58	-0.55
Debt	11.5	0.58	1.4	-0.52	1.53	0.29
Avg. int. rate	22.96	-0.31	0.013	-0.96	13.63	-0.43

the bond prices during a recession or an expansion for a middle-income of the youngest age cohort. As one can see, the debt level where borrowers are likely to default does not change. If lenders perceived enough increased risk to making a loan, they would endogenously tighten their borrowing constraints which would trigger more defaults.

### **Experiment 2 - Income Shocks + Intermediation Shocks**

In an attempt to reconcile the standard model with the empirical observations, we introduce intermediation shocks. In the second experiment, we vary the risk-free cost of saving between 2% and 6% with aggregate state. This variation in the cost of borrowing is not calibrated to any particular fact in the data, but simply intended to represent a large change in financial system during recessions which will drive up the cost of borrowing.

Figure 4.3: Bond Prices: Expansion vs. Recession



We show the results in the last column of Table 4.5. The increased borrowing costs makes it more difficult to borrow during recessions, as a result there are more defaults. This type of shock reduces the gap between the model and the data. Indeed, intermediation shocks can generate pro-cyclical borrowing. It also increases the volatility of both filings and interest rates, albeit somewhat mechanically.

These experiments demonstrate the potential importance of the lending market during recession for consumers. However, the benchmark model still understates the volatility of bankruptcy filings.

## Summary

A standard quantitative model modified to include a cyclical income process generates filing and consumption cyclicalities consistent with the data. However, this simple model cannot generate pro-cyclicality of consumer debt observed in the data. The model also dramatically understates the cyclical volatility of filings and interest rates. The basic reason for both these failures is that most households in the model are able to weather mild income shocks induced by a recession by borrowing to smooth consumption over time. Thus, recessions in such a model are accompanied by an increase in debt and only very mild increase in bankruptcy filings. And since bankruptcy rates in the model are very stable, so are the interest rates, as can be seen in Figure 4.3. One way of thinking about this failure of the model is that the endogenous lending standards in the model do not respond enough to the aggregate shocks.

Introducing financial intermediation shocks (exogenously increasing the cost of funds during recessions) enables the basic model to reproduce pro-cyclicality of consumer debt observed in the data. Mechanically, increasing the cost of borrowing during recessions limits ability of households to smooth their idiosyncratic shocks over time, and leads to both fall in debt and an increase in bankruptcy filings in a recession. Furthermore, this exogenous mechanism directly affects variability of interest rates. Yet, even with the exogenous financial intermediation shocks, the model struggles to generate large volatility of bankruptcy filings.

## 4.5 Conclusion and Future Work

We document the historical cyclical behaviour of several key characteristics of the consumer credit market. We find that unsecured debt is (mostly) procyclical, while delinquencies, charge-offs, bankruptcies, and average interest rates are counter-cyclical and very volatile. We construct and analyze a quantitative model of consumer borrowing and bankruptcy, where agents face idiosyncratic income and expense shocks and the economy is subject aggregate income distribution and financial intermediation shocks, to explain the facts. We calibrate the model and compare its predictions to the data. We use the model to decompose the driving forces behind cyclical fluctuations in the consumer credit market and their impact on defaults. The most standard model (without intermediation shocks) misses the data in two key dimensions. First, our quantitative experiments reveal that the standard model generates counter-cyclical debt despite matching the cyclicity of filings and consumption in the data. Second, the standard model fails to generate the large cyclical volatilities of filings and interest rates observed in the data.

The model's ability to match the data is greatly improved by introducing "intermediation shocks." Jermann and Quadrini [2012] argue that real and financial variables are affected by "financial shocks," which affect one's ability to raise capital. Jermann and Quadrini [2012] find these shocks to be counter-cyclical. To match this, we exogenously vary the cost of funds borrowers face.

Incorporating these intermediation shocks into the benchmark model generates pro-cyclical debt. Furthermore, the cyclical volatilities of filings and interest rates become closer to the data. Thus, we argue that counter-cyclical intermediation shocks may play an important role in consumer credit markets.

This work highlights a key challenge for future research. First, the model with intermediation shocks still struggles to reproduce the volatility of filings. The quantitative model studied in this chapter suggests that cyclical variation in idiosyncratic income shocks cannot generate large volatility of bankruptcy filings, not even when combined with intermediation shocks. But this is inconsistent with the empirical findings of the previous chapter, which documents that unemployment rates are very important to explaining bankruptcy rates. Reconciling these findings is an important avenue for future research.

Our data analysis also uncovers a period where the cyclicality of debt switches. While credit is mostly pro-cyclical, this pattern does not hold in the 1990s. It is possible that the secular changes in the consumer credit market, which lead to the dramatic rise in personal bankruptcies and consumer credit, explain this phenomenon. Further research is needed to establish whether the cyclicality of debt could have switched during transition to the new steady state.

## 4.6 Bibliography

- ADDA, J., AND R. COOPER (2003): *Dynamic Economics*. MIT Press, Cambridge, Massachusetts.
- AGARWAL, S., AND C. LIU (2003): “Determinants of Credit Card Delinquency and Bankruptcy: Macroeconomic Factors,” *Journal of Economics and Finance*, 27(1), 75–84.
- BACCHETTA, P., AND S. GERLACH (1997): “Consumption and Credit Constraints: International Evidence,” *Journal of Monetary Economics*, 40, 207–238.
- BUTRICA, B. A., H. M. IAMS, AND K. E. SMITH (2004): “The Changing Impact of Social Security on Retirement Income in the United States,” *Social Security Bulletin*, 65(3), 1–13.
- CAIN, J. M. (1997): “Proving Fraud in Credit Card Dischargeability Actions: A Permanent State of Flux,” *Commercial Law Journal*, 102(3), 233–255.
- CARROLL, C., AND A. SAMWICK (1997): “The Nature of Precautionary Wealth,” *Journal of Monetary Economics*, 40(4), 41–71.
- CHATTERJEE, S., D. CORBAE, M. NAKAJIMA, AND J. V. RÍOS-RULL (2007): “A Quantitative Theory of Unsecured Consumer Credit with Risk of Default,” *Econometrica*, 75(6), 1525–1589.
- CORBAE, D., AND P. DERASMO (2013): “A quantitative model of banking industry dynamics,” *manuscript*. University of Maryland at College Park.
- EATON, J., AND M. GERSOVITZ (1981): “Debt with Potential Repudiation: Theoretical and Empirical Analysis,” *Review of Economic Studies*, 48(2), 289–309.
- GORDON, G. (2013): “Evaluating Default Policy: The Business Cycle Matters,” UIndiana University, mimeo.

- GOURINCHAS, P.-O., AND J. PARKER (2002): "Consumption over the Life Cycle," *Econometrica*, 70(1), 47–89.
- HODRICK, R. J., AND E. C. PRESCOTT (1997): "Postwar U.S. Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking*, 29(1), 1–16.
- HUBBARD, R., J. SKINNER, AND S. P. ZELDES (1994): "The Importance of Precautionary Motives in Explaining Individual and Aggregate Saving," *Carnegie-Rochester Conference Series on Public Policy*, 40, 59–125.
- JERMANN, U., AND V. QUADRINI (2012): "Macroeconomic Effects of Financial Shocks," *American Economic Review*, 102(1), 238–71.
- KRUSELL, P., AND A. A. SMITH (1998): "Income and Wealth Heterogeneity in the Macroeconomy," *Journal of Political Economy*, 106, 867–896.
- LIVSHITS, I., J. MACGEE, AND M. TERTILT (2007): "Consumer Bankruptcy: A Fresh Start," *American Economic Review*, 97, 402–418.
- LIVSHITS, I., J. MACGEE, AND M. TERTILT (2010): "Accounting for the Rise in Consumer Bankruptcies," *American Economic Journal: Macroeconomics*, pp. 165–193.
- LUDVIGSON, S. (1999): "Consumption and Credit: A Model of Time-Varying Liquidity Constraints," *Review of Economics and Statistics*, pp. 434–447.
- MECHAM, L. R. (2004): *Bankruptcy Basics*. Administrative Office of the United States Courts.
- NAKAJIMA, M., AND J.-V. RÍOS-RULL (2005): *Frontiers in Applied General Equilibrium Modeling: In Honor of Herbert Scarf* chap. Default and Aggregate Fluctuations in Storage Economies, pp. 127–150. Cambridge University Press.
- RAVN, M. O., AND H. UHLIG (2002): "On adjusting the Hodrick-Prescott filter for the frequency of observations," *The Review of Economics and Statistics*, 84(2), 371–375.
- STORESLETTEN, K., C. TELMER, AND A. YARON (2004): "Consumption and Risk Sharing over the Life Cycle," *Journal of Monetary Economics*, 51, 609–633.
- SULLIVAN, J. X. (2008): "Borrowing During Unemployment: Unsecured Debt as a Safety Net," *Journal of Human Resources*, XLIII, 383–412.



- SULLIVAN, T. A., E. WARREN, AND J. L. WESTBROOK (2000): *The Fragile Middle Class*. Yale University Press, New Haven and London.
- WARREN, E. (2002): "Financial Collapse and Class Status: Who Goes Bankrupt?," *Osgoode Hall Law Journal*, 41, 115–146.
- WEINBERG, J. A. (1995): "Cycles in lending standards?," *ECONOMIC QUARTERLY-FEDERAL RESERVE BANK OF RICHMOND*, 81, 1–18.
- WELLS, W., J. KURTZ, AND R. CALHOUN (1991): "The Implementation of Bankruptcy Code Section 707(b): The Law and the Reality," *Cleveland State Law Review*, pp. 15–48.
- WHITE, M. (2007): "Bankruptcy Reform and Credit Cards," *NBER Working Paper No. 13265*.

## Chapter 5

### Conclusion

My dissertation consists of three chapters in macroeconomics. Chapter 2 examines the role of cross-sector complementarities in driving the observed patterns of innovation activity in the United States economy. Chapters 3 and 4 study consumer credit, and in particular, bankruptcy. Chapter 3 is an empirical paper examining the drivers of bankruptcy filings using Canadian data. In chapter 4 a quantitative macroeconomic model explains consumers' decisions to declare bankruptcy and how this is impacted in a recession. The model is then calibrated to fit the observed patterns of bankruptcies in United States. Each chapter documents new empirical facts. Chapters 2 and 4 also provide new economic models to try to explain these new findings.

In Chapter 2, I propose that innovation is related between industries due to the production structure. When the quality of available ideas improves in one industry, the output of that industry will increase, which leads to increased

demand in the complementary industry. This increases the returns from inventing in the second industry, and results in their inventors developing ideas below the prior quality threshold. I develop a multi-industry innovation model to capture this mechanism. I also provide evidence that the inter-industry relationship strengthens with a measure of complementarities between any two industries.

These findings suggest that production complementarities between industries are an important determinant of innovation, which had not been previously considered. They also contribute to the current debate on U.S. patent policy, where there is a growing belief among scholars and practitioners that the quality of patents has declined during their recent surge in number. This viewpoint largely attributes the surge in patents to their increased value in deterring competition. It is well-documented that the rate of patenting has increased in most industries [Kortum and Lerner, 1999]. This observation is consistent with an explanation involving changes in the patent system. However, I instead use the model to demonstrate that such a decline could be explained by increased innovative opportunities in certain industries and the corresponding response of complementary industries.

The other two chapters explore the forces affecting consumer bankruptcies during recessions. The chapters on consumer credit highlight a key challenge for future research. In Chapter 4, the quantitative model's ability to match the

data is greatly improved by introducing “intermediation shocks.” Nevertheless, it struggles to reproduce the volatility of filings observed in U.S. data. The implication is that the cyclical variation in idiosyncratic income shocks cannot generate large enough volatility of bankruptcy filings, not even when combined with intermediation shocks. But this is inconsistent with the empirical findings of the previous chapter, which documents that unemployment rates are very important to explaining bankruptcy rates in Canada. Reconciling these findings is an important avenue for future research.

## 5.1 Bibliography

Samuel Kortum and Josh Lerner. What is behind the recent surge in patenting? *Research Policy*, 28(1):1–22, January 1999. URL <http://ideas.repec.org/a/eee/respol/v28y1999i1p1-22.html>.

# Appendix A

## Chapter 2 Appendix

### A.1 Cutoff Derivation

The final good sector is perfectly competitive, thus:

$$R_i = 0.5X_i^{-\frac{1}{\epsilon}}(0.5X_1^{1-\frac{1}{\epsilon}} + 0.5X_2^{1-\frac{1}{\epsilon}})^{\frac{1}{\epsilon-1}}.$$

Using (2.7) it must be that for each industry  $i$  that

$$0.5\left(0.5\left(\frac{ka_1^k}{(k-1)\phi_1^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}} + 0.5\left(\frac{ka_2^k}{(k-1)\phi_2^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{\epsilon-1}}\left(\frac{ka_1^k}{(k-1)\phi_1^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_1 = 1. \quad (\text{A.1})$$

Dividing (A.1) for  $i = 1$  and  $i = 2$ ,

$$\begin{aligned} \left(\frac{ka_1^k}{(k-1)\phi_1^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_1 &= \left(\frac{ka_2^k}{(k-1)\phi_2^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_2 \\ \Leftrightarrow \left(\frac{a_1^k}{\phi_1^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_1 &= \left(\frac{a_2^k}{\phi_2^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_2 \\ \Leftrightarrow a_1^{-\frac{k}{\epsilon}}\phi_1^{1+\frac{k-1}{\epsilon}} &= a_2^{-\frac{k}{\epsilon}}\phi_2^{1+\frac{k-1}{\epsilon}} \\ \Leftrightarrow \phi_2 &= \left(\frac{a_2}{a_1}\right)^b\phi_1, \end{aligned} \quad (\text{A.2})$$

where  $b = \frac{k}{\epsilon+k-1}$ .

Notice that

$$\begin{aligned}
R_1\phi_1 &= 0.5\left(0.5\left(\frac{ka_1^k}{(k-1)\phi_1^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}} + 0.5\left(\frac{ka_2^k}{(k-1)\phi_2^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{\epsilon-1}}\left(\frac{ka_1^k}{(k-1)\phi_1^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_1 \\
&= 0.5\left(0.5\left(\frac{a_1^k}{\phi_1^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}} + 0.5\left(\frac{a_2^k}{\phi_2^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{\epsilon-1}}\left(\frac{a_1^k}{\phi_1^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_1 \\
&= 0.5\left(0.5\left(\frac{1}{\phi_1^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}} + 0.5\left(\frac{a_2^k}{\underbrace{a_1^k\phi_2^{k-1}}_{(*)}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{\epsilon-1}}\left(\frac{1}{\phi_1^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_1
\end{aligned} \tag{A.3}$$

By substituting (A.2) into (\*), we get

$$\frac{a_2^k}{a_1^k\phi_2^{k-1}} = \frac{a_2^k}{a_1^k\left(\left(\frac{a_2}{a_1}\right)^b\phi_1\right)^{k-1}} = \frac{a_2^{k-b(k-1)}}{a_1^{k-b(k-1)}\phi_1^{k-1}}.$$

Substituting (A.3) into the above expression, we get

$$\begin{aligned}
&0.5\left(0.5\left(\frac{1}{\phi_1^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}} + 0.5\left(\frac{a_2^{k-b(k-1)}}{a_1^{k-b(k-1)}\phi_1^{k-1}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{\epsilon-1}}\left(\frac{1}{\phi_1^{k-1}}\right)^{-\frac{1}{\epsilon}}\phi_1 \\
&= 0.5\left(0.5 + 0.5\left(\frac{a_2^{k-b(k-1)}}{a_1^{k-b(k-1)}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{\epsilon-1}}\phi_1 \\
&= 0.5 \cdot 0.5^{\frac{1}{\epsilon-1}}\left(1 + \left(\frac{a_2^{k-b(k-1)}}{a_1^{k-b(k-1)}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{\epsilon-1}}\phi_1 \\
&= 0.5^{\frac{\epsilon}{\epsilon-1}}\left(1 + \left(\frac{a_2^{k-b(k-1)}}{a_1^{k-b(k-1)}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{\epsilon-1}}\phi_1 = 1
\end{aligned}$$

Therefore,

$$\begin{aligned}
\phi_1 &= 0.5^{\frac{\epsilon}{1-\epsilon}}\left(1 + \left(\frac{a_2^{k-b(k-1)}}{a_1^{k-b(k-1)}}\right)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{1}{1-\epsilon}} \\
&= 0.5^{\frac{\epsilon}{1-\epsilon}}\left(1 + \left(\frac{a_2}{a_1}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}}\right)^{\frac{1}{1-\epsilon}}.
\end{aligned}$$

## A.2 Proof of Proposition 4

**Proof.** Consider the weighted quality of each industry:

$$Q_i^w = Q_i \frac{N_i}{N_i + N_j} = \frac{k\phi_i \left(\frac{a_i}{\phi_i}\right)^k}{(k-1)\left(\left(\frac{a_i}{\phi_i}\right)^k + \left(\frac{a_j}{\phi_j}\right)^k\right)} = \frac{k\phi_i}{(k-1)\left(1 + \left(\frac{a_j}{a_i} \frac{\phi_i}{\phi_j}\right)^k\right)}$$

Notice

$$\frac{\phi_i^*}{\phi_j^*} = \left( \frac{\left(\frac{a_j}{a_i}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1}{\left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1} \right)^{\frac{1}{1-\epsilon}} = \left( \frac{a_j}{a_i} \right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} = \left( \frac{a_i}{a_j} \right)^{\frac{k}{\epsilon+k-1}}.$$

Then

$$Q_i^w = \frac{k\phi_i}{(k-1)\left(1 + \left(\frac{a_i}{a_j}\right)^{\frac{k(1-\epsilon)}{\epsilon+k-1}}\right)} = \frac{k\left(\left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1\right)^{\frac{1}{1-\epsilon}}}{(k-1)\left(1 + \left(\frac{a_i}{a_j}\right)^{\frac{k(1-\epsilon)}{\epsilon+k-1}}\right)} = \frac{k\left(\left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1\right)^{\frac{\epsilon}{1-\epsilon}}}{(k-1)}$$

Furthermore,

$$\frac{\partial Q_i^w}{\partial a_i} = -\frac{k^2 e \left(\left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1\right)^{\frac{2\epsilon-1}{1-\epsilon}} \left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}}}{(\epsilon+k-1)(k-1)a_i}$$

and

$$\frac{\partial Q_j^w}{\partial a_i} = \frac{k^2 e \left(\left(\frac{a_j}{a_i}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1\right)^{\frac{2\epsilon-1}{1-\epsilon}} \left(\frac{a_j}{a_i}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}}}{(\epsilon+k-1)(k-1)a_i}.$$

Then  $\frac{\partial Q}{\partial a_i}$  is positive iff

$$\begin{aligned} & \left(\frac{a_j}{a_i}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1 \left(\frac{a_j}{a_i}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} > \left(\left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1\right)^{\frac{2\epsilon-1}{1-\epsilon}} \left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} \\ \Leftrightarrow & \left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} \left(\frac{a_j}{a_i}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} > \left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} \left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} \\ \Leftrightarrow & a_i^{\frac{k(2\epsilon-1)}{\epsilon+k-1}} \left(\frac{a_j}{a_i}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} > \left(\frac{a_i}{a_j}\right)^{\frac{k(2\epsilon-1)}{\epsilon+k-1}} \left(\frac{a_i}{a_j}\right)^{\frac{k(\epsilon-1)}{\epsilon+k-1}} \\ & a_i^{\frac{k}{\epsilon+k-1}} > a_j^{\frac{k}{\epsilon+k-1}}. \end{aligned}$$

■

## A.3 Special Cases

### Example 2. Perfect Complements

When  $\epsilon = 0$ , aggregate quality is invariant to idea distributions. To see this, I consider how aggregate quality changes by decomposing it into the contribution from each industry. Notice, a Leontif production function implies that the weighted quality of industry  $i$  equals

$$\frac{Q_i N_i}{N_i + N_j} = \frac{Q_i N_i}{N_i + \frac{Q_i N_i}{Q_j}} = \frac{1}{\frac{1}{Q_i} + \frac{1}{Q_j}}.$$

Then average aggregate quality is

$$Q = \frac{2}{\frac{1}{Q_i} + \frac{1}{Q_j}}.$$

Now, the distributional assumptions provide a stark implication. Since the average quality in each industry is proportional to marginal cost,

$$\frac{1}{\frac{1}{Q_i} + \frac{1}{Q_j}} = \frac{k}{k-1} \left( \frac{1}{\frac{1}{\phi_i^*} + \frac{1}{\phi_j^*}} \right) = \frac{k}{k-1}.$$

But

$$\frac{1}{\frac{1}{\phi_i^*} + \frac{1}{\phi_j^*}} = 1,$$

because the marginal benefit must equal the marginal cost. Therefore average aggregate quality is invariant to the idea distributions.

The intuition is that, any change in project quality for a industry is exactly offset by its weight among projects. Thus the industry with worse ideas must produce more of them, because of complementarities.

### Example 3. Perfect Substitutes

When  $\epsilon = +\infty$ , aggregate quality is also invariant to idea distributions. In this case, each marginal project must be able to produce a unit of the final good. Thus

$$\frac{1}{\phi_i^*} = \frac{1}{2}.$$



This implies that the average quality for each industry is identical:

$$Q_i = \frac{2k}{k-1}.$$

Conversely to Example 2, in this case the industry with better ideas implements more of them.

## A.4 Patent Number and Quality by Industry

Table A.1: Patent Number and Quality by Industry

Industry	Total Patents	Ave. Cites	R&D/Sales	Name
13	8048	12.2	1.9%	Oil And Gas Extraction
20	5344	10.5	0.6%	Food And Kindred Products
22	1526	11.4	0.6%	Textile Mill Products
23	403	10.1	0.4%	Finished Products Made From Fabrics And Similar Mat.
24	1170	6.8	0.7%	Lumber And Wood Products, Except Furniture
25	2234	7.8	1.2%	Furniture And Fixtures
26	13580	12.2	4.4%	Paper And Allied Products
27	1140	9.5	0.1%	Printing, Publishing, And Allied Industries
28	88758	9.6	4.4%	Chemicals And Allied Products
29	25304	8.1	0.6%	Petroleum Refining And Related Industries
30	7271	8.2	2.4%	Rubber And Miscellaneous Plastics Products
31	325	12.1	0.1%	Leather And Leather Products
32	3973	8.2	1.2%	Stone, Clay, Glass, And Concrete Products
33	8046	8.8	1.4%	Primary Metal Industries
34	7836	11.9	1.3%	Fabricated Metal Products, Except Machinery And Trans. Equipment
35	65274	9.4	4.6%	Industrial And Commercial Machinery And Computer Equipment
36	73988	10.3	4.8%	Electrical Equipment And Components, Except Comp. Equip.
37	58091	10.0	3.8%	Transportation Equipment
38	44023	10.9	5.5%	Instrument and Related Products
39	2495	8.8	2.1%	Miscellaneous Manufacturing Industries
48	14311	21.0	2.9%	Communications
49	959	12.8	0.0%	Electric, Gas, And Sanitary Services

## A.5 Other Types of Patents

The NBER database includes all (and only) utility patents. In addition to utility patents, there Design, Reissue, and Plant patents. Hall et al. [2001] finds that utility patents accounts for 90% of all patents. Utility patents are granted only if the invention provides an identifiable benefit and that is capable of use. Design patents are issued for a new, original, and ornamental design embodied in or applied to an article of manufacture. Plant patents are issued for a new and distinct, invented or discovered asexually reproduced plant including cultivated sports, mutants, hybrids, and newly found seedlings, other than a tuber propagated plant or a plant found in an uncultivated state. Reissue Patent are issued to correct an error in an already issued utility, design, or plant patent.

## A.6 Bibliography

Bronwyn H. Hall, Adam B. Jaffe, and M. Trajtenberg. The nber patent citation data file: Lessons, insights and methodological tools. *NBER working paper*, 2001.

# Appendix B

## Chapter 3 Appendix

### B.1 Income Imputation

We impute income average-tax family income from the SFS. To make the data comparable, we restrict the SFS sample to individuals who do not run a business. We then regress average family income on balance sheet, socio-demographic, expenses and provincial dummies for four different age cohorts (25-34,35-44,45-54,55-65). The results are presented in Table B.1.

To generate the results in Section , we take the following steps:

1. Calculate mean for variables in Table B.1 in 2004 \$.
2. Impute average family income for the population of filers based the means from the above model.
3. Adjust imputed income for real (annual) income growth for the relevant age group.

As a check of shifts in the distribution of projected filer income, we compare the ratio of mean versus median income. As can be seen from Table B.2, this ratio is quite consistent over the recession.

Table B.1: After-Tax Family Income Regression

	(1)	(2)	(3)	(4)
	Income	Income	Income	Income
Non-Financial Net Worth	0.103 (0.0677)	0.144** (0.0460)	0.128*** (0.0303)	0.0963*** (0.0267)
Property Value	0.0674*** (0.0121)	0.00676** (0.00235)	0.0511*** (0.00733)	0.0333*** (0.00611)
No Property	1236.7 (3181.9)	-7781.0* (3636.0)	-10857.9*** (3144.7)	-6784.8* (2983.7)
Vehicle Value	0.500*** (0.0874)	0.421*** (0.103)	0.271*** (0.0722)	0.362*** (0.0696)
Mortgage Debt	0.0784 (0.0700)	0.201*** (0.0482)	0.0612 (0.0406)	0.0922* (0.0398)
Non-Mortgage Debt	0.132 (0.0763)	0.169* (0.0717)	0.216*** (0.0488)	0.217*** (0.0555)
Housing Expenses	0.742*** (0.217)	1.070*** (0.210)	1.286*** (0.210)	0.487* (0.207)
Cohabitation	12705.0*** (2089.4)	15395.2*** (3126.3)	20953.0*** (2491.0)	17066.5*** (2630.8)
Male	5416.9** (1880.1)	5550.3 (2889.6)	6263.5** (2224.6)	6900.9** (2373.0)
Few Assets	-9342.2** (3103.5)	-7842.5 (4638.7)	-4773.6 (3881.7)	-6454.0 (3873.6)
Atlantic	11998.7** (4543.4)	16103.8** (5840.1)	4794.3 (4211.7)	19385.8*** (4188.2)
Quebec	14534.7*** (3805.1)	17169.8*** (4484.5)	21978.9*** (3492.9)	15732.9*** (3118.7)
Ont	18223.9*** (4077.1)	20262.6*** (4677.4)	19433.0*** (3605.4)	23224.1*** (3256.8)
Prairies	20325.8*** (3979.8)	25493.9*** (5151.5)	20338.8*** (3874.5)	19530.0*** (3842.6)
BC	10147.2* (4713.5)	17483.9** (5501.6)	14353.6** (4346.8)	11984.6** (4159.7)
Observations	571	844	822	651
Adjusted $R^2$	0.844	0.732	0.829	0.821

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.2: Projected Income: Median and Mean

Age Group	Period	Median	Mean	Mean/Median
24-34	2005	26917	26947	1.001
	1st Quarter	28717	28751	1.001
	2nd Quarter	31150	30965	0.994
	3rd Quarter	31398	31443	1.001
	4th Quarter	30899	30948	1.002
35-44	2005	29925	29993	1.002
	1st Quarter	33594	33495	0.997
	2nd Quarter	37461	36889	0.985
	3rd Quarter	38339	38381	1.001
	4th Quarter	38682	38743	1.002
45-54	2005	29860	29666	0.994
	1st Quarter	31225	31269	1.001
	2nd Quarter	33554	33425	0.996
	3rd Quarter	34866	34811	0.998
	4th Quarter	34183	34252	1.002
55-64	2005	39596	39512	0.998
	1st Quarter	42003	42460	1.011
	2nd Quarter	46658	46338	0.993
	3rd Quarter	47239	47393	1.003
	4th Quarter	46622	46651	1.001

## B.2 Data Sources

Table B.3: Data Sources

Variable	Source
Unemployment	Cansim Table 282-0087, Table 282-0001
Average of Bank rate	Cansim - Table 176-0043
Consumer loan rate	Cansim - Table 176-0043
Mortgage lending rate - 5 year	Cansim - Table 176-0043
Prime Business Rate	Cansim - Table 176-0043
Consumer credit	Cansim - Table 378-0051
Mortgages credit	Cansim - Table 378-0051
Liabilities	Consumer + Mortgages
Disposable Income	Cansim - Table 380-0019, Table 384-0035
Credit Card Delinquencies	CBA
Population	Cansim Table 051-0026, Table 051-0001
Insolvency Rate	OSB
Bankruptcies	OSB, Cansim Table 177-0001, 177-0003, ?
Assets and Liabilities of Bankruptcy Filers	Cansim Table 177-0001, 177-0003
Senior Loan Officer Survey	Bank of Canada
U.S. Senior Loan Office Survey	US Board of Governors
Housing Prices	Teranet
CPI	Cansim 176-0003
Weekly Effective Interest Rate	Bank of Canada

## **B.3 Bibliography**

Bronwyn H. Hall, Adam B. Jaffe, and M. Trajtenberg. The nber patent citation data file: Lessons, insights and methodological tools. *NBER working paper*, 2001.



# **Appendix C**

## **Chapter 4 Data Sources**

Table C.1: Data Sources

Variable	Source	Note
GDP	BEA	Real, Billions
Personal Disposable Income	BEA	Nominal, Billions
Unemployment Rate	BLS	
Employment Rate	BLS	
Population	Census	Resident Population
Households	Statistical Abstracts	Thousands
CPI (Urban US)	BLS	
Bankruptcy Filings	ABI	
Revolving & Nonrevolving Credit	BOG -G19	Millions
Interest Rate	BOG -G19	Annual
Charge-off rates, credit card	FDIC	
Delinquencies, credit card	BoG - FFIEC	
Federal fund rate	BOG - H15	
Consumption	BEA	Billions
LIBOR	IMF-IFS	3 Month
3 Month T-Bills	BOG - H15	
Treasury securities	BOG - H15	5 year
Consumer Liabilities	BOG Z.1	Nominal
Mortgage Liabilities	BOG Z.1	Nominal

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