Does Economic Insecurity Affect Employee Innovation?

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Abstract

We explore whether economic insecurity, stemming from declines in housing wealth during the 2008 financial crisis, affects the propensity of employees to pursue risky projects at work. We examine this question through the lens of technological innovation, using a unique dataset that links inventors patenting output with their housing transactions. We find that employees that experienced a negative shock to their housing wealth during the crisis pursued less risky and less innovative projects relative to others in the same firm and metropolitan area. The effects are more pronounced among employees with limited outside labor market opportunities, and among employees who had little equity in their house before the crisis. In contrast, housing price run-ups did not affect employee risk taking. Overall, these findings are consistent with a career concerns model in which negative housing wealth shocks lead to lower employee failure tolerance due to costly default concerns and therefore reduced risk taking within the firm. In contrast to the view that innovation policy is dictated by top executives, the results also highlight the importance of the "bottom-up" view, in which employees failure tolerance affect firm innovation.

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1 Introduction

Over the past several decades, the annual proportion of households in the U.S. experiencing a severe economic loss has been steadily increasing, peaking with the recent financial crisis (Hacker et al., 2014). The effects of such wealth fluctuations on household choices such as consumption and savings have been carefully studied in the literature (e.g., Poterba et al., 1995; Dynan et al., 2004; Case et al., 2005; Campbell and Cocco, 2007; Mian et al., 2013). However, largely unstudied is the extent to which such wealth shocks affect the behavior of employees, in particular, their willingness to engage in productive yet risky tasks. In this paper, we investigate how economic insecurity affects employee risk-taking through the lens of technological innovation, a particularly risky type of activity, which has been recognized since Solow (1957) to be a critical driver of economic growth and productivity.

Much of the literature on the drivers of innovation has focused on macro- or firm-level factors. However, it is ultimately individual employees who must undertake innovative projects. Moreover, because firms cannot perfectly observe ability and effort, employees may bear exposure to the success or failure of these projects. Individuals who pursue innovations that are successful may be rewarded in terms of wages, promotions, and job-security. Conversely, those who pursue innovations that fail to pan out, may be worse off along the same dimensions. Taking these risks into account, an employee may choose to tilt their work toward safer projects that exploit their firm's existing knowledge base, or toward riskier projects that explore new technologies (Manso, 2011). This raises the question of whether an employee's own financial situation might impact the riskiness of their selected projects.

To study this question, we focus on housing, a major component of household wealth. We examine the effect of the decline in house prices during the 2008 financial crisis, which was a particularly severe shock that led to increased economic insecurity for many employees. Specifically, we examine whether employees who experienced major declines in housing wealth during the crisis altered the riskiness of the innovative projects they pursued as a result.

How might a decline in housing wealth affect employee innovation? If firms provide full insurance to their employees against house price movements, or if employees have no control over project selection, declines in housing wealth may have no effect. However, if firms cannot fully insure against such shocks, or employees have a degree of autonomy, then this null hypothesis may not hold. In that case, it is theoretically ambiguous whether employees would pursue safer or riskier projects in response to a negative house price shock.On the one hand, employees may pursue safer projects if they worry that losing their job would force them into costly foreclosure. Employee preferences may also be such that they become more risk-averse following a negative wealth shock and therefore tilt their labor income to a less risky profile. Relatedly, the anxiety and stress associated with wealth shocks may further increase risk aversion. On the other hand, housing price declines may lead employees to pursue riskier projects, particularly if they become underwater on their mortgage and believe the prospects of profitable price recovery are slim. In that case, they will be less motivated to by a desire to maintain regular mortgage payments and thus less concerned about pursuing safe projects that ensure job security.

Ultimately, the impact of housing wealth shocks on project selection and risk-taking is an empirical issue. To tackle this question, we construct a unique dataset that links patent inventors in firms with their housing transactions from deed records. From the patent data we can observe the characteristics of the projects pursued by inventors. Specifically, we can observe the quantity and quality of inventors' innovative output. In addition, we can also observe whether inventors' projects appear relatively safe in the sense that they exploit their firms' existing knowledge, or risky in the sense that they explore new technologies. From the deed records we can observe the exact location of an inventor's house, as well as characteristics such as square-footage, and number of bedrooms. These data allow us to exploit very localized house price shocks as well as to control for detailed house characteristics.

Of course, the key empirical challenge is that the location of an inventor's house is not randomly assigned. Absent a causal effect, there may be other reasons that those who live in areas harder hit during the crisis also experience a change in their innovative output. For example, it may be that those who live in harder hit areas tend to work at firms that are themselves more affected by the crisis. In particular, firms in crisis-affected areas may experience a decline in local demand, or a tightening of financial constraints stemming from the decline in the value of their real estate collateral Chaney et al. (2012). It is also possible that firms located in crisis-affected areas simply tend to be ones that were changing their innovation strategy during this time period for reasons unrelated to the decline in local house prices. To address these issue, our analysis compares only inventors working at the same firm—who are therefore similarly affected by firm-level changes in demand, borrowing capacity, or innovation strategy—but who are exposed to different house price shocks.

However, additional concerns may arise within firms. Firms can have multiple divisions that are scattered geographically, and may specialize in different technologies. Thus, it is possible that even among inventors at the same firm, those who live in more crisis-affected areas also tend to work in divisions of the firm that are more affected in terms of innovative opportunities. To address this concern, we further restrict our analysis to only compare inventors who both work at the same firm and also live in the same core based statistical area (CBSA). For most firms, this implies that we are comparing inventors working at the same local office. Despite the fact that such inventors live in the same area, there remains substantial variation in the house price shocks they experience because we exploit house price shocks at the zip code level. Thus, we can identify the effect of house prices movements among these otherwise similar inventors.

Overall, we find that negative shocks to housing wealth do significantly impact project selection and risk taking among inventors. Inventors who experience a negative shock produce fewer patents and patents of lower quality based on citations. We also find that inventors who suffer losses in housing wealth during the financial crisis are less likely to patent in technologies that are new to their firm. More generally, they are also less likely to draw on information from outside their firm's existing knowledge base. These inventors also produce narrower innovations, combining information from fewer disparate fields as observed by having patents with lower generality and originality scores. This evidence is consistent with inventors pursuing low risk research that exploits existing firm knowledge following a negative wealth shock. We find similar effects even conditional on inventors remaining in the same firm throughout the post-crisis period. Thus, our results do not appear to be driven by inventors with high exposure to the crisis becoming non-research-active due to unemployment, retirement, death, promotion, or movement to a less research-oriented firm.

For robustness, we verify that our results hold when comparing inventors who not only work at the same firm and live in the same area, but who also specialize in the same narrow technology class at the onset of the crisis based on their patenting history. Furthermore, to address the concern that certain types of inventors systematically sort into zipcodes which were differentially affected by the crisis and that such inventors decreased the riskiness of their research during the crisis for reasons unrelated to housing price declines, we show that our results are robust to a battery of specifications with fixed effects controlling for inventor, neighborhood, and housing characteristics. These include, for example, firm by CBSA by age fixed effects and firm by CBSA by zipcode income level fixed effects. We show that, regardless of specification, our estimated effects are robust to such controls.

Finally, we explore the channel through which our results operate. We find that inventors who specialize in popular technologies, with thicker labor market opportunities, experience a smaller decline in risk taking projects when housing prices collapse, in contrast to inventors with thinner labor market opportunities. We also find that inventors who bought their house before the bubble (before 2005), and therefore likely to have positive equity after the crash, experience a smaller decline in their risk taking activities. Finally, when exploring the house price boom in 2002, we find that housing prices increases do not correlate with inventors behavior. Put together, these results are consistent with the channel of costly default, in which inventors pursue safer projects when the value of their home declines because they worry that losing their job would force them into costly foreclosure. These results are also consistent with an alternative channel in which declines in housing wealth increases employee anxiety that lead employees to pursue safer projects.

This paper is related to several strands of the literature. There have been a variety of papers that examine the determinants of firm innovation. These papers include Harhoff (1999), Hall et al. (2005), Lerner et al. (2011), Manso (2011), Aghion et al. (2013), Ferreira et al. (2014), Seru (2014), Manso (2016), and Bernstein (2015b). These papers focus on the impact of corporate governance, capital structure, ownership concentration, and other factors on innovation at the firm level. For the most part, this literatures suggest a "top-down" view of firm innovation, wherein it is driven by firm level factors set by those at the top of the organization. In contrast, our results suggest that that there is also a "bottom-up" component as well, in the sense that household shocks to individual inventors affect the types of projects a firm pursues. To our knowledge, this paper is the first to directly study how household level shocks impact innovation.

This paper also relates to a recent literature which examines the impact of local house price movements on firm investment. Chaney et al. (2012) show that negative real estate shocks decrease collateral value and reduce the investment of public firms. Adelino et al. (2015) show that the collateral channel is particularly important for small businesses. Our channel is very different. We control for the collateral channel at the firm level with our fixed effects and instead argue that house price movements affect employee incentives and their willingness to take risk.

Finally, this paper also relates to a strand of the literature that explores the relationship between household leverage and labor supply (as in Bernstein, 2015a, Mulligan (2008; 2010; 2009), Herkenhoff and Ohanian (2011), and Donaldson et al. (2015)). In that literature, the focus is largely on debt overhang and the decision of whether to work or not. Conversely, our focus is on inventors who are already employed and the impact of household leverage on project selection within the firm, and the willingness to take risks at their job.

The rest of the paper paper proceeds as follows. Section 2 discusses potential channels through which housing wealth shocks might affect risk taking. Section 3 describes our data and Section 4 details our empirical strategy. Our results are presented in Section 5. Section 6 concludes.

2 Housing Wealth and Risk Taking - Potential Channels

If employees have no control over project selection, or alternatively, employees are fully insured against declines in housing wealth, then changes in housing prices may have no effect. However, if these two assumptions do not hold, then fluctuations in house prices may lead employees to adjust the riskiness of their innovative activities within the firm. At one end of the innovation spectrum, employees may choose to *expolit* existing technologies, ensuring mediocre payoffs with high probability. At the other end, they may choose to *explore* new and untested technologies that could potentially lead to high payoffs buthave a low probability of success (Manso, 2011). Pursuing exploratory innovation is potentially risky for employees because firms cannot directly observe talent or effort(Holmstrom, 1989). As a result, employees who pursue exploratory research risk that their firm may assess them as unskilled and unproductive in the case of failure, which may affect their their likelihood of getting a raise, being promoted, or even being able to retain their current job. We illustrate these trade-offs in a simple career concerns model in the spirit of Holmström (1999) in Section A.1 of the Appendix.

Below, we propose four potential channels through which declines in housing wealth might affect the riskiness of projects that employees undertake and the nature of their innovation. First, the prospect of costly mortgage default may affect risk-taking incentives, even for a risk-neutral employee. Second, for a risk-averse employee, declines in housing wealth may directly affect risk-aversion through the structure of the employee's utility function. Third, risk-taking may be affected simply by the mental stress and anxiety associated with major wealth losses. Finally, employees who are underwater on their mortgage may have different risk-taking incentives as a result. We consider all four channels to be interesting, and attempt to disentangle them empirically to the extent possible later in the paper.

2.1 Costly Default

If default costs are high, inventors may pursue exploitation following a major decline in house prices due to concerns that failed exploration could lead to job loss and subsequent foreclosure . While foreclosure is always a concern, employees may be more concerned following a major house price decline because they may be underwater and no longer have the option of refinancing or selling if they run into trouble making their mortgage payments.

2.2 Decreasing Risk-Aversion

A negative shock to house prices may also affect employee risk-taking by directly increasing risk-aversion. In particular, employees who have utility functions that exhibit decreasing absolute risk-aversion (e.g., CRRA utility) will bemore risk-averse after experiencing a drop in wealth due to housing price declines. This may lead to employees to pursue more exploitative innovation rather than exploratory. Survey evidence supports the assumption of decreasing absolute risk aversion (e.g., Guiso and Paiella, 2008). In addition, it has also been shown that risk-aversion can increase with the prospect of being liquidity constrained (Gollier, 2000) and by the presence of additional uninsurable, nondiversifiable risks (Pratt and Zeckhauser, 1987; Kimball, 1993; Eeckhoudt et al., 1996). Interestingly, in the latter case, the literature usually considers the effect of high exogenous labor income risk on individuals' propensity to hold risky assets in their financial portfolio. In our setting, one could instead think about the effect of housing wealth declines on individuals' propensity to take risks with their labor income.

2.3 Anxiety

Risk-taking may also be affected simply by the mental stress and anxiety associated with major wealth losses. For example, Engelberg and Parsons (2016) find a strong link between daily stock returns and hospital admissions due to psychological conditions such as anxiety and panic disorder. Currie and Tekin (2015) find that increases in foreclosures are associated with significant increases in unscheduled urgent care visits. They argue that homeowners facing foreclosure risk are "in over there heads" and likely to find their situation stressful. In a related work, Deaton (2012) finds that during the financial crisis, Americans reported a sharp increase in worry and stress. A number of studies suggest that such increases in stress and anxiety could decrease risk-taking (e.g., Maner et al., 2007; Gambetti and Giusberti, 2012; Giorgetta et al., 2012). For example, Gambetti and Giusberti (2012) find that anxiety leads to more conservative financial investments and reduced likelihood of engaging in worthwhile risk-taking activities. Hence, it may be the case that increased anxiety due to housing wealth losses leads employees to pursue more exploitative and less risky innovation.

2.4 Underwater Incentives

Finally, declines in housing prices could also lead to a more exploratory innovation and risk taking if default costs are sufficiently low but house prices are expected to eventually recover. In that case, employees that experience a significant decline in housing wealth may in fact pursue riskier projects than those employees that experience a small decline in housing prices. To see this, note that inventors with positive equity in their home would have an incentive to pursue safer projects so as ensure job security, to maintain their ability to make scheduled mortgage payments, and thereby take full advantage of the expected recovery in house prices. However, inventors with negative equity in their home due to price declines would have less to gain from any expected potential recovery. This may lead to employees who are underwater on their mortgage to pursue more exploratory innovation rather than exploitative. In Section A.2 of the Appendix we formally model this channel and the costly default channel above using a variant of the Holmström (1999) work on incentive provision through career concerns.

3 Data

3.1 Data Sources and Sample Selection

As discussed in the previous section, theoretically, housing prices decline may lead to either a decrease or an increase in employee risk taking behavior within firms. We thus turn to data to resolve the question. We obtain data on all US patents granted from 1976 through 2015 directly from the United States Patent and Trademark Office (USPTO). The USPTO data provide information on the date a patent was applied for and ultimately granted, the individual(s) credited as the patent's inventor(s), the company to which the patent was originally assigned, and other patents cited as prior work. One challenge the data presents is that it lacks consistent identifiers for patent inventors and companies. In order to identify inventors and companies over time, we rely on two large-scale disambiguation efforts. The first is an inventor disambiguation provided by Benjamin Balsmeier et al. (2015). Their algorithm combines inventor names, locations, co-authors, associated companies, and patent classifications to create an inventor identifier. While Benjamin Balsmeier et al. also provide a company identifier, they state that it is much less accurate and mainly created as a crude input for the inventor disambiguation. Therefore, for company disambiguation, we instead rely on the NBER patent data project. The NBER company identifier is based on a word frequency algorithm that ranks matches more highly if they share unusual words. Because the NBER data end in 2006, we extend it forward based on code that they provide.[1]

The USPTO patent data contain the city and state of residence for patent inventors. Inventors also provide the USPTO with their full residential address on a signed oath as well as a patent application data sheet (ADS). Images of at least one of these forms are generally available starting in 2001 via the USPTO's Patent Application Information Retrieval (PAIR) portal. We download all of the relevant image files and apply optical character recognition (OCR) to make the text machine readable. Addresses are too irregular to extract consistently, however we are able to parse out zip codes coinciding the the inventor's city of residence. To identify property owned by a patent inventor, we combine the patent data with CoreLogic. CoreLogic tracks housing transactions in the United States based on deed records as well as other sources. This makes it possible to construct the full ownership history of a given house. We match inventors to houses based on first name, last name, middle initial, city, zip code, and patent application date. This procedure yields a 35% unique match rate. The unmatched inventors either did not own a house, purchased a house before CoreLogic's coverage of their county, or were unmatchable due to name spelling irregularities (e.g., nicknames) on their patent application and/or deed. For matched inventors, we can observe detailed house characteristics as well as mortgage characteristics.

Having matched inventors to houses, we next add in data on house price movements. Most house price indices aggregate at the city level due to the large volume of transactions needed to construct

[1] https://sites.google.com/site/patentdataproject/

a constant-quality index. This allows for high-frequency measurement, but at the cost of smoothing the considerable variation that is present within a city. We are interested in comparing inventors that work at the same establishment of a firm, but who own houses in different local areas. Therefore, we use a zip code level price index constructed by Bogin et al. (2016), which overcomes the volume issue by reducing to an annual frequency. The index is based on the repeat-sales methodology and thus measures house price movements unrelated to changes in house quality. For robustness we also use a similar index constructed by Zillow, which makes use of their proprietary house price estimates for non-traded houses.[2]

Together, we construct an annual inventor-level panel. In each year we observe an inventor's innovative output along with the location of the inventor's house and a price index associated with that location. It should be noted that one shortcoming of the data is that we are unable to observe certain inventor characteristics during years in which the inventor has zero patents. For example, if an inventor changes employers we can only observe the change the next time the inventor patents. In order to ensure that we are studying inventors that are still active and that our information about them is not too stale, we limit our sample to inventors that had at least one patent in the three years preceding the 2008 financial crisis. This leaves us with observations on 162,076 inventors.

3.2 Key Variables

We use patent-based measures of an inventor's innovative output (Jaffe and Trajtenberg, 2002; Lanjouw et al., 1998)that have been widely adopted over the past two decades.[3] Our primary measure of the quantity of an inventor's innovative output is the number of granted patents the inventor applied for in a given year. Such a measure, however, likely captures both an inventor's effort as well as her willingness to take on risk. In particular, inventors likely have many low-risk but productive activities they can engage in that do not have the potential of resulting in a patent. Thus patenting, in and of itself, can be viewed a measure of risk-taking. A key challenge in our

[2] http://www.zillow.com/research/data/

[3] Recent examples include Lerner et al. (2011); Aghion et al. (2013); Seru (2014).

empirical design is therefore to find patent-based measures that capture the riskiness of the research design. Guided by the idea that more groundbreaking research is also riskier at the outset, we begin by measuring the number of citations the inventors patents receive on a per patent basis. Patent citations are important in patent filings since they serve as "property markers" delineating the scope of the granted claims. Hall et al. (2005) illustrate that citations are a good measure of innovation quality and economic importance. Specifically, they find that an extra citation per patent boosts a firm's market value by 3%. Moreover, Kogan et al. (2012) show that the stock market reaction to patent approvals is a strong predictor of the number of future citations a patent receives. One challenge in measuring patent citations is that patents granted at the end of the sample period have less time to garner citations than those granted at the beginning. In addition, citation rates vary considerably over time and across technologies. To address both of these issues, we normalize each patent's citation count by the average citation count for all other patents granted in the same year and 3-digit technology class.

Since citations tend to be highly skewed, we furthermore construct a simple indicator variable equal to one if a patent was in the top 10% of patents from the same year and technology class in terms of citations received. Such an approach is followed by Azoulay et al. (2010) in their study of the incentives to undertake risky research in the academic life sciences. Continuing in the spirit of Azoulay et al. (2010), we not only examine the quantity and quality of the research pursued, but also the nature and direction of the research. For example, it is likely risker for an inventor to pursue research ideas outside of the firm's usual agenda or to draw on ideas outside of the firm's existing knowledge base. We therefore define a simple "New class" indicator variable equal to one if the patent is in a technology class the inventor's firm has never patented in before. Following Brav et al. (2016), we also define a patent as "exploratory" if less than 20% of the patents it cites are not existing knowledge from the point of view of the inventor's firm. Existing knowledge is defined as all patents the firm was granted in the past five years as well as all patents the firm cited in the same time frame.

Finally, research that seeks to synthesize or draw from the ideas many disparate fields likely has a more uncertain outcome than research which confines itself to a single area of study. In a related fashion, research which has the ability to make a broad impact across a wide variety of fields is also likely to be of a more difficult, riskier sort than research which is only of interest to a narrow subset of researchers. To pursue these ideas, we examine changes in the "Originality" and "Generality" of an inventor's patents. We define these variables following Trajtenberg et al. (1997). In particular:

$$Generality_i = 1 - \sum_{j}^{n_i} s_{ij}^2,$$

where s_{ij} denotes the percentage of citations received by patent i that belong to patent class j, out of n_i patent classes. Note, the sum is the Herfindahl concentration index. Thus, if a patent is cited by subsequent patents that belong to a wide range of fields the measure will be high, whereas if most citations are concentrated in a few fields the measure will be low. A high generality score thus suggests that the patent had a widespread impact in that it influenced subsequent innovations in a variety of fields. Azoulay et al. (2010) also use a similar measure. "Originality" is defined the same way, except that it refers to citations made. Thus, if a patent cites previous patents that belong to a narrow set of technologies the originality score will be low, whereas citing patents in a wide range of fields would lead to a high score. These measures tend to be positively correlated with the number of citations made or received. When there are more citations, there is a built-in tendency to cover more patent classes. To correct for this tendency we apply a bias adjustment suggested by Hall et al. (2001). As before, we also normalize each patent's generality or originality by the mean generality or originality for all other patents granted in the same year and 3-digit technology class.

3.3 Summary Statistics

In Panel A of Table 1 we compare innovation measures during the 3-years before the crisis (years 2005-2007) and the subsequent 5-year period from 2008 onward that capture inventors productivity during the crisis. It is interesting to note that inventor productivity has declined substantially during the crisis. While the log average number of patents in the pre-crisis period was 1.15, after the crisis this number declined almost by half to 0.645. Moreover, it is also evident that inventors became less likely to explore new technologies during the crisis. The probability of patenting in a new technology class has declined from 26% in the pre-crisis period to only 8.69% during the crisis. This is also evident in the decline in the log number of exploratory patents, and the generality and originality of patents produced during the crisis, when compared to the pre-crisis period.

In Panel B of Table 1 we show the list of the top 20 most populated technologies in our sample. The most common category is computer hardware and software, capturing 11.8% of the inventors in our sample, and communication is in the second category with 10.21% of the inventors. Other common technologies include drugs, chemicals, semi-conductor devices, etc. In Panel C of Table 1, we report the correlation between the different measures of inventor productivity during crisis. In almost all cases the correlations between the different measures are significantly low, and this is not surprising given the different approaches taken to construct them. There are a few exceptions however. For example, as expected, a top patent is also a highly cited patent, and a top patent is also likely to be a very general one as well, that is, cited by a broad set of technologies. This confirms the intuition that highly cited patents, are also broad patents, as measured by generality and originality, and also likely to be defined as exploratory patents, as we discuss above.

4 Empirical Strategy

Our primary interest is in how changes in house prices associated with the 2008 financial crisis affect the project selection and risk taking of inventors. Because the 2008 crisis is a one time event that affects all inventors in our sample simultaneously, we rely on cross-sectional variation in which we compare innovative output across inventors living in zip codes that experienced differential house price shocks. To fix ideas, we begin by considering the following estimating equation:

$$y_{i,post} = \beta * \triangle\% HP_{z,post} + \delta * y_{i,pre} + \epsilon, \tag{1}$$

where i indexes inventors, and z indexes zip codes. The pre-period is defined as 2005–2007 and the post period is defined as 2008–20012. The variable $y_{i,post}$ represents the various patent-based measures of innovative output discussed in Section 3.2, including the total number of patents produced by inventor i, the number of citations per patent, measures of exploratory activity, etc. The variable $\triangle\%HP_{z,post}$ represents the percent change in the house price index during the post period for zip code z in which inventor i owned a house.

Equation 1 poses several potential concerns, as the location of an inventor's house is not randomly assigned. For example, it may be that those who live in harder hit areas tend to work at firms that are more affected by the crisis. One might naturally expect that to be that case as firms in crisis-affected areas are likely to experience a decline in local demand. It should be noted, however, that the innovative firms we study generally serve a national or global market. Another reason local house prices could affect firm innovation is that a decline in local house prices may reduce borrowing capacity for firms that rely on real estate collateral (Chaney et al., 2012). Finally, it is also possible that firms located in crisis-affected areas simply tend to be ones that were changing their innovation strategy during this time period for reasons unrelated to the decline in house prices. To address these various issues, we begin by including firm fixed effects in all of our estimations. With the inclusion of firm fixed effects, we are identifying off of inventors that worked at the same firm but lived in areas with differential house price declines during the crisis. Such inventors are arguably similarly affected by firm level changes in demand, borrowing capacity, or innovation strategy.

However, it remains possible that firms have divisions in multiple regions. In this case, divisions of the same firm that are in harder hit regions may tend to be the ones that are affected by changes in local demand or the ones that change their innovation strategy. To address this issue, we refine our specification even further by including firm by core based statistical area (CBSA) fixed effects.[4] Assuming that the firms in our sample have only one office in the area surrounding a given city,

[4]CBSAs are comprised of Metropolitan Statistical Areas (MSA) and Micropolitan Statistical Areas. Essentially they are counties surrounding urban clusters both large (>50,000) and small (10,000–50,000). Not every county in the United States is located within a CBSA, as CBSAs do not include rural areas situated far from a significant urban cluster. Most of the inventors in our sample do reside in a Metropolitan or Micropolitan Statistical Area, however for those that do not, we define their local area simply by county. Thus, for rural inventors, our CBSA fixed effects are effectively county fixed effects.

these fixed effects will be equivalent to office fixed effects. Note that with firm by CBSA fixed effects we are identifying off of inventors that worked at the same firm and owned a house in the same metropolitan area, but who experienced differential price declines in their respective zip codes.

This approach provides several advantages. First, the workers we compare are likely to be similar, as they operate in the same labor market, and are facing similar work opportunities outside of their firm. These workers are also likely to be similar given that they chose to live in the same general area. Finally, since they likely work in the same office of the same firm, they will likely be subject to the same division-level innovation policy. Following the discussion above, in our baseline analysis we estimate equations of the form:

$$y_{i,post} = \beta * \triangle\% HP_{z,post} + \delta * y_{i,pre} + \eta_{f,c} + \epsilon, \tag{2}$$

where the key change relative to equation 1 above is the addition of $\eta_{f,c}$, which represents represent firm by CBSA fixed effects. Note that with firm by CBSA fixed effects, we will only have power to estimate the key coefficient, β, if there is sufficient variation in house price shocks experience by workers in the same firm and CBSA. Figure 1 provides evidence that such variation is indeed present in the data. Panel A shows that there is substantial variance in house price movements during the crisis across zip codes within a CBSA. Moreover, Panel B shows that inventors also tend to live in such metropolitan areas with high variance.

Even under this specification, however, one may worry that firms may have multiple offices within a metropolitan area, perhaps focusing on different technologies. While this is unlikely to be the case, we can provide a further refinement to our specification. In robustness tests, we show that all our results hold with firm by CBSA by technology class fixed effects. By including these fixed effects, we essentially compare the innovative productivity of two inventors who work at the same firm, reside in the same CBSA, and patent in similar technologies, but who experience different house price shocks during the crisis. The technology classes are based on the USPTO classification scheme. This classification scheme is comprised of approximately 400 different categories, and thus is very detailed. For example, just within the "Data Processing" area, there are different classes that capture "Artificial Intelligence," "Vehicles and Navigation," "Generic Control Systems," and "Database and File Management."

Still, it remains possible that even within the same firm and CBSA, different types of employees sort into neighborhoods that are differentially exposed to the crisis. Such sorting could bias our results to the extent that those inventors selecting into neighborhoods which were hardest hit by the crisis, were also those inventors who decreased (or increased) the riskiness of their research during the crisis for reasons unrelated to their house price decline. To address these concerns, we run a battery of robustness tests controlling for additional fixed effects which address potential selection stories. These additional fixed effects reflect both inventor characteristics as well as zipcode-level neighborhod characteristics. As an example, to address the concern that younger workers tend to systematically live in the city center, while older workers live in suburbia, we include firm by CBSA by age fixed effects. To address the concern that more productive, higher-wage earners sort into richer neighborhoods, we include firm by CBSA by zipcode income level fixed effects. Section 5.3 provides greater detail on these specifications and discusses a variety of other such robustness tests. Our results remain virtually unchanged with the inclusion of these controls.

Finally, to further address the concern that our results are driven by sorting of different types of workers into different zip codes within a CBSA, we take advantage of the fact that the effect of house price shocks on innovative output is likely to be smaller for some subgroups relative to others. In particular, if the mechanism posited by our model is correct, house price shocks should be less important for inventors who face a thick outside labor market based on their field of expertise. These inventors will be less concerned about loosing their job when hit with a negative house price shock because finding a new job will be more difficult. Similarly, house price shocks should be less important for those who bought their house at inflated prices before the bubble. These inventors will be less concerned about losing their job when hit with a negative house price shock because they will have more home equity. Motivated by these observations, we estimate variants of Equation 2 of the form:

$$y_{i,post} = \beta * \triangle\%HP_{z,post} \times Characteristic_i + \gamma * Characteristic_i + \delta * y_{i,pre} + \eta_f + \eta_z + \epsilon, \quad (3)$$

where $Characteristic$ is an inventor level characteristic such as an indicator for whether the inventor specialized in a popular technology, or an indicator for whether the inventor bought before the bubble period. This specification allows us to test for heterogeneity in the effect of house price shocks. Evidence of such heterogeneity would be consistent with the mechanism posited by our model. An important additional benefit of this specification is that it also allows us to include zip code fixed effects, η_z, which controls for differences among inventors who choose to live in different zip codes. While the main effect of $\triangle\%HP$ is subsumed by the zip code fixed effects, we can estimate the coefficient β on the interaction term. In this case, β represents the differential effect of house price shocks for those with $Characteristic = 1$ relative to those with $Characteristic = 0$. Essentially, we can control for unobservable differences among inventors who choose to live in different zip codes because two inventors who live in the same zip code should respond differently to the same house price shock.

5 Results

5.1 Main Findings

We begin in Table 2 by estimating variants of Equation 2. In columns 1–2 we first examine the effect of changes in local house prices on the number of patents an inventor produces. We include the number of patents produced in the pre-crisis period as a control, to capture changes in productivity relative to the pre-crisis baseline. In addition, we also include firm by CBSA fixed effects, meaning that we identify off of variation from inventors that work at the same firm and own a house in the same area, but live in different zip codes. Comparing such inventors further helps to minimize selection concerns, as these inventors are likely to be similar. In column 1 we estimate a positive coefficient that is statistically significant at the 1% level. This indicates that a greater decline in local house prices where an inventor lives is strongly associated with lower patenting productivity. In column 2 we also include as an additional control the change in house prices that an inventor's zip code experienced leading up to the crisis. Our main coefficient of interest changes little when controlling for house price appreciation during the run up to the crisis, and in fact we find that pre-crisis price changes have no statistically significant relation to patenting during the post-crisis period. Therefore, our results do not seem to be driven by selection of certain types of inventors into more "bubbly" areas within a CBSA. The differences we find only coincide with ex-post price movements, which were presumably hard to predict and thus to select on ex-ante. As will be shown in Section 5.3, we also find that our estimates remain unchanged after controlling for technology within the firm and additional inventor and house characteristics, which further cuts against a selection story. The effects are economically as well as statistically significant. A one standard deviation decline in house prices during the crisis is estimated to have led to a 4.0% decline in the number of patents produced.

In columns 3–4 of Table 2 we examine the effect of house price declines on patent quality as captured by citations per patent. We again estimate a positive coefficient on the change in local house prices in an inventor's zip code, significant at the 1% level. Thus, not only do house price declines lead to a reduction in the quantity of patents produced, the quality those patents also appears to be lower. In terms of magnitudes, a one standard deviation decline in house prices coincides with approximately a 7.9% decline in patent citations. Finally, in columns 5–6 we find very similar results when patent quality is instead measured simply as the number of patents produced that are in the top 10% in terms of citations relative to other patents granted in the same year and technology class. A one standard deviation decline in house prices leads to an 8.9% decline in top patents.

To explore how the effects change with the intensity of the house price declines, we separate our house price change variable into ten decile indicator variables and re-run the analysis, letting the top decile (highest percentage change) be the omitted category. The results are presented in Figure

2. As one would expect, we see that the results are strongest in the hardest hit areas and that the effect monotonically declines for the most part as the size of the housing price decline decreases. The effect still remains statistically significant until the 60th percentile of house price changes, though.

Next, we investigate more directly the extent to which our results might reflect a tendency for inventors to "play it safe" after being hit with a major shock to outside wealth. For example, losing her job may force an inventor to sell her house at a loss, or even undergo a forclosure. Thus, inventors who own a house in a harder hit area may face less failure tolerance in the spirit of Manso (2011). However, unlike in Manso (2011), failure tolerance here is not driven by the terms of a contract with one's employer, but by external conditions beyond the employer or employee's control. Nonetheless the same reasoning applies. That is, a reduction in failure tolerance may reduce incentives for exploration (creation of new knowledge) and instead create incentives for exploitation (profiting from existing knowledge). The reason is that pursuing exploration is risky and if an inventor is not successful in doing so, he or she may be perceived to be less talented.

To investigate this, in columns 1–2 of Table 3 we examine whether the patents of inventors that experience larger house price declines during the crisis rely more heavily on the existing knowledge of their firm. As discussed in Section 3.2, we define a patent to be "exploratory" if less than 20% percent of the patent's citations are to other patents granted to their firm or cited by their firm in recent years. Consistent with the idea that inventors pursue less exploration when they experience a negative shock to their outside wealth, we find that those living in harder hit zip codes produce fewer exploratory patents. Specifically, a one standard deviation decline in house prices leads to a 9.6% decline in exploratory patents. In addition, in columns 3–4 we also find that larger house price declines are associated with a reduction in the tendency to patent in a technology class that is new to an inventor's firm, with a one standard deviation fall in house prices causing a 7.14% decline in the likelihood of patenting in a new technology class. Since all of the results are *within firm*, they cannot be driven simply by a change in firm policy away from exploration during the crisis for firms located in harder hit regions.

In Table 4 we further investigate the nature of innovations produced by inventors living in areas differentially affected by the crisis. In this case we focus on generality and originality. As discussed in Section 3.2, a high generality score indicates that the patent influenced subsequent innovations in a variety of fields; a high originality score indicates that the patent made use of prior knowledge from a wide variety of fields. One could argue that these measures also reflect exploration in the sense that a patent that combines knowledge across different areas is likely riskier to attempt to produce from the point of view of an inventor. Consistent with Table 4, we find that inventors in zip codes with larger price declines also create less general and less original patents in the post-crisis period. A one standard deviation decline in house prices leads to a 5.6% fall in generality and a 4.2% fall in originality.

As illustrated in Panels (c) through (f) of Figure 2, the effect of housing prices on risk taking and the tendency to pursue exploratory projects is again strongest in the hardest hit areas. Moreover, the effect monotonically declines for the most part as the size of the housing price decline decreases.

5.2 Inventors Remaining at the Same Firm

Do these effects arise from changes in the incentives of inventors working within a firm? An alternative explanation is that the changes in innovative output that we document arise from periods of unemployment, or transitions to different firms. In fact, it might be the case that those who experience a negative house price shock move to firms with less risky innovation policies. To explore whether our results are driven by changes in the incentives of inventors working within a firm, we repeat our baseline analysis among inventors who remain at the same firm. We identify inventors as "stayers" if all the patents they produce in the first three years after the crisis are assigned to the same firm they worked at in 2007. We also rely on LinkedIn searches to further verify that these inventors remained at the same firm during the crisis.

If changes in innovative output arise only from inventors who leave their pre-crisis firm and potentially sort into to different types of new firms, we would expect to find no effect among stayers. However, and in contrast to this view, we find that our main results hold for the inventors that remained in the same firm in the post-crisis period as well. The results of this exercise are presented in Table 5. As we observe in the previous analysis, we find that stayers who experienced a decline in housing prices produce fewer patents and patents of lower quality. Moreover, such inventors choose less exploratory projects which are also less general and original in nature. Thus, the changes in project selection occur for inventors that remain at the same firm and are not due firm transitions or long periods of unemployment. Moreover, since this analysis conditions on being an active inventor in the post-crisis period while in the same firm, this analysis also implies that the results are not driven by inventors becoming non-research-active due to retirement or death.

5.3 Selection Concerns

In this section, we investigate a variety of possible selection concerns and show that our results are robust to the inclusion of additional fixed effects designed to control for them.

5.3.1 Technology

One potential concern is that we might be comparing inventors that work at the same firm and live in the same CSBA, but do not work in the same division of the firm. If those who live in more crisis-affected areas also tend to work in divisions experiencing greater declines in exploratory innovation for unrelated reasons, that would bias our estimates. To address this possibility, we try including firm by CBSA by inventor technology class fixed effects. The results are in Row 2 of Table 6, Panel A. We define an inventor's technology class to be the modal 3-digit class of the inventor's patents in the pre-period. This specification is very conservative in that it only identifies off of variation from inventors that work at the same firm, specialize in the same narrow technology class, and live in the same CBSA. Even under this very stringent specification, we estimate similar effects as before.

5.3.2 Inventor Characteristics

Another concern is that, among inventors that work at the same firm and live in the same CBSA, there may be still be sorting across zip codes based on individual inventor characteristics. In this subsection, we address a variety of possible selection stories and show that none of them can account for our estimated effects. For example, one such selection story is that less experienced inventors lived in zip codes which were disproportionately impacted by the housing crisis. It is plausible that less experienced employees may also have been more concerned about being terminated during the Great Recession, which thus impacted their willingness to take risks. Alternatively, firms may have cut back on innovation during the Great Recession and re-assigned the least experienced inventors to projects less focused on important, cutting-edge innovation. To address this possibility, for each inventor we calculate experience as the number of years, as of 2007, since the inventor's first patent and sort inventors into experience quartiles. We then re-run our regressions with firm by CBSA by experience fixed effects. This specification compares two inventors of similar experience level, working at the same firm, and living in the same CBSA. We report the results in Row 3 of Table 6, Panel A. Our results are very similar to the baseline specification.

Similar to experience, it may be that younger inventors, less educated inventors, or inventors in less senior positions were more worried about termination or were more likely to be re-assigned to less innovative roles within the firm. It is also plausible that younger inventors tend to systematically live in different zip codes than older inventors. For instance, younger workers may be more likely to live in the city center, while older workers tend to live more in the suburbs. Similarly, inventors in more senior positions likely have higher wages and may therefore tend to live in richer zip codes. Our patent data, however, does not provide information regarding age, education, or position. We therefore merge these data with public LinkedIn profiles available through Google searches according to inventor name and company name. This cuts our sample size approximately in half, but as Row 1 of Table 6, Panel B demonstrates, the results of our baseline specification using only the LinkedIn sample remain quite consistent.

The LinkedIn data provide information on inventor age, education, employment history, and position within the firm. We calculate age as the number of years, as of 2007, since the inventor's first degree, plus 22. We then sort inventors into quartiles based on age. For education, we define a series of dummy variables based on the highest degree obtained (BA, MA, MBA, JD, MD, PhD). We say that an inventor has a senior position if one of the following words appears in the position title: manager, director, president, VP, chief, CEO, CTO, management, executive, principal, partner, chairman, manager, head, or chair. Row 2 of Table 6, Panel B runs our regressions with firm by CBSA by age fixed effects. Row 3 of Table 6, Panel B runs them with firm by CBSA by education fixed effects. Row 4 of Table 6, Panel B shows the results with firm by CBSA by senior position fixed effects. In all specifications, the estimated effects are similar to the baseline results.

Our data does not directly provide us with information regarding wages. To the extent that there is differential sorting based on wages and that inventors with higher wages responded to the Great Recession differently that inventors with lower wages, our results could be biased. Moreover, inventors with children may tend to live in different neighborhoods than single inventors and may also be less willing to take on job-related risks during economic downturns. Our first attempt to control for these concerns is to include fixed effects based on the square-footage of the house the inventors own in 2007. It seems likely that inventors with higher wages and those with children would, on average, live in larger houses. Therefore, in Row 5 of Table 6, Panel A we sort inventors into quartiles based on the square-footage of the house owned in 2007 and run the regressions with CBSA by firm by square-footage fixed effects. This specification compares two inventors working at the same firm, living in the same CBSA, and living in houses of comparable size. Once again, the results are very similar to the baseline estimates.

5.3.3 Neighborhood Characteristics

In this section, as further robustness checks, instead of controlling for inventor level characteristics which might impact sorting into different types of neighborhoods, we directly control for various neighborhood level features. We begin by controlling for the income level of the zipcode in which an inventor lives. This specification further addresses the concern that inventors with higher wages may sort into richer neighborhoods and may also have differential concerns regarding job termination during economic downturns. In Row 4 of Table 6, Panel A we sort inventors into quartiles based on the 2000 mean income level of the zipcode in which they live and then run our regressions with

CBSA by firm by neighborhood income fixed effects. These regressions compare two inventors who work at the same firm, live in the same CBSA, and live in zipcodes of similar mean income level. The results are very consistent with our baseline specification.

In Row 7 of Table 6, Panel A we sort inventors into quartiles based on the number of children in their resident zipcode, as reported by the 2000 census and run our regressions with CBSA by firm by zipcode family size fixed effects. This specification is yet another check for the concern that inventors with children, who likely sort into more family-oriented neighborhoods, were more concerned about job termination during the Great Recession. To further address this point, in Row 6 of Table 6, Panel A we sort inventors into quartiles based on the 2000 census measure of how urban their resident zipcode and then include CBSA by firm by zipcode urban measure fixed effects. It seems likely that single inventors put less of a premium on space and are thus likely to live in the city center than inventors with families. In both specifications, our estimates are very similar to the baseline results.

5.4 Evidence on the Channel

As described in Section 2, there are several potential channels through which a negative shock to housing wealth may affect employee risk-taking. Based on our results thus far, we can already rule out the *underwater incentives* channel, described in Section 2.4. Recall that, under this channel, we hypothesize that employees that experience a large house price decline may take on *more* risk because—having negative home equity—they benefit less from a potential price recovery and so are less concerned with avoiding default. In contrast, we find that employees that experience a large house price decline take on *less* risk.

This still leaves three remaining potential channels through which declines in housing wealth may lead to less exploration and risk taking: *costly default, decreasing risk-aversion,* and *anxiety.* We believe the effect of wealth shocks on employee innovation that we have documented thus far are novel and interesting, even without pinning down the precise channel through which they operate. Nonetheless, we attempt to do so to the extent possible below.

To separate the three channels conceptually, when we consider the pure decreasing risk-aversion channel, we think about employees who face zero default costs (including psychological) and no anxiety. When we consider the pure costly default channel, we think about employees who are risk-neutral and suffer no anxiety (except for the psychological costs of default). When we consider the pure anxiety channel, we think about employees who are risk-neutral and face zero default costs (including psychological). Of course the three channels are not mutually exclusive, and they are difficult to disentangle empirically.

5.4.1 Labor Market Opportunities

We begin by examining whether the strength of our baseline results varies with employees' outside labor market opportunities. In particular, we classify employees as specializing in widely-used technologies or narrowly-used technologies. Presumably, there is a thicker labor market for inventors specializing in widely-used technologies, making it easier for them to find another job if necessary. Under the pure decreasing risk-aversion channel, outside labor market opportunities should be irrelevant. Two employees with the same utility function, who have experienced the same decline in wealth, should have the same increase in risk-aversion—even if one faces a thicker labor market than the other. Under the pure anxiety channel, it is also not clear that the employee with better outside labor market opportunities should experience less anxiety from the same wealth decline once we assume that default has zero psychological costs. However, under the pure costly default channel, one might expect there to be a smaller effect of the decline in housing wealth for the employee who faces the thicker labor market. This employee is less likely to be unemployed for an extended period of time should she lose her job and thus less likely to face foreclosure.

To test whether the effect of house prices varies with the popularity of an inventor's field of specialty, we classify technologies as popular or not based on patenting in the pre-period. Specifically, we define an inventor's field of specialty based on the modal technology class of the inventor's patents in the five years leading up to the crisis. We classify a technology as popular if it is in the top quartile in terms of the total number of inventors specializing in it over the same time period. We then estimate Equation 3, which interacts house price shocks with the popular technology indicator. As highlighted in Section 4, we are also able to include zip code fixed effect in this specification, which further help to address selection concerns. Essentially, we can control for unobservable differences among inventors who choose to live in different zip codes by taking advantage of the fact that two inventors who live in the same zip code may respond differently to the same house price shock due to different outside labor market opportunities.[5] Table 7 shows the results. Across almost all of our outcomes, we estimate a significant negative coefficient on the interaction term. This indicates that the effect of house price movements is indeed smaller for inventors who work in popular technologies. These results are consistent with the costly default channel.

5.4.2 Negative Home Equity

Next, we examine whether the strength of our baseline results varies with when employees bought their house. Inventors who bought their house during the bubble (just before the crisis) are more likely to have ended up with low or negative home equity after the crash since they had little time to accumulate equity and prices were likely to have been particularly inflated (while leverage was cheap). In contrast, those who bought earlier are more likely to have retained and accumulated significant equity. Under the pure decreasing risk-aversion channel, it is again not clear whether it should matter when employees bought their house, assuming they retain positive home equity. Two such employees will experience the same absolute decline in wealth when they are exposed to the same house price decline. Under DARA utility, for example, this means they will experience the same decline in risk tolerance. However, if employees who bought their house during the bubble have negative home equity after the crash, their wealth losses are capped, in contrast to employees who bought their house earlier and therefore would absorb the entire shock. Hence, in that case, we may expect that employees that bought their house earlier may suffer from a greater wealth losses and consequently a greater increase in risk-aversion. On the other hand, the costly default channel would predict the opposite. That is, if costly default is employees' main concern, the effect should

[5]Due to power limitations, we are not able to include firm by CBSA fixed effects as well in this specification. However, we do include continue to include firm fixed effects.

be largest for employees who bought during the bubble and thus ended up with low or negative equity after the crash. Finally, under the pure anxiety channel, it is again not clear that when employees bought their house should matter.

Motivated by the discussion above, we again estimate Equation 3 with zip code and firm fixed effects, this time interacting house price shocks with an indicator equal to one if the inventor bought their house prior to 2005. Table 8 shows that across almost all of our outcomes, we estimate a significant negative coefficient on the interaction term. This indicates that the effect of house price movements is indeed smaller for inventors who bought their house earlier and at a lower price. These results are again most consistent with the costly default channel.

5.4.3 The Effect of the Housing Boom

The results thus far have focused on the decline in house prices associated with the financial crisis. In this section we explore the effect of increases in house prices during the boom leading up to the crisis from 2002 to 2007. Therefore, we explore in this analysis whether the effect of housing wealth on risk taking and innovation is symmetric.

Under the pure decreasing risk-aversion channel, we would expect that employees that experienced a larger increase in housing wealth would have a greater appetite for risk, thus leading to a higher degree of employee exploration. Similarly, increases in housing wealth should decrease anxiety, leading to more exploration under the anxiety channel. In contrast, under the costly default channel we would expect to find no effect on employee risk taking, because employees with significant home equity would have no concerns about default.

We turn to estimating Equation 2, our baseline specification that includes CBSA X Firm fixed effects. This time, we focus on a sample of inventor homeowners that have at least a single patent in the years 1999-2001 and explore how subsequent house price changes, during the boom period of 2002-2007, affect employee innovation and risk taking. Table 9 shows that all there is no effect of house price changes for any of our outcomes during the boom period. These results are inconsistent with the risk aversion channel as well as the anxiety channel. However, these results are consistent with the costly default channel, which predicts an asymmetric effect of house price increase and decreases.

6 Conclusion

In this paper, we investigate whether household level shocks impact employee project selection and risk taking within firms. The household level shocks that we focus on are changes in housing wealth experienced by employees during the financial crisis. We examine employee project selection and risk-taking through the lens of innovation. Using matched data on patent inventors and housing transactions, we find that employees who experience a negative shock to housing wealth during the financial crisis produce fewer patents and patents of lower quality relative to others in the same firm and in the same metropolitan area. They are also less likely to patent in technologies that are new to their firm or more generally to draw on information from outside of their firm's existing knowledge base. Similarly, their patents combine information from fewer disparate fields and are used by a narrower set of technologies.

We show that these results are consistent with a career concerns model in which negative house price shocks lead to lower failure tolerance and therefore reduced incentives for exploratory innovation. Interestingly, in our setting, failure tolerance is driven by by external conditions rather than the terms of a contract with one's employer. Following a major house price decline, inventors want to play it safe to avoid costly default and foreclosure. Consistent with this mechanism, we find that our estimated effects are strongest in thin labor markets, where finding a new job is most difficult. Thus, while much of the innovation literature emphasizes the importance of firm level factors along with the strategy set by top executives, the evidence presented here suggests that shocks to individual employees also have a significant impact on the types of projects a firm pursues.

References

Adelino, Manuel, Antoinette Schoar, and Felipe Severino, "House prices, collateral, and self-employment," *Journal of Financial Economics*, August 2015, *117* (2), 288–306.

Aghion, Philippe, John Van Reenen, and Luigi Zingales, "Innovation and institutional ownership," *American Economic Review*, 2013, *103* (1), 277–304.

Azoulay, Peter, Joshua S. G. Zivin, and Gustavo Manso, "Incentives and Creativity: Evidence from the Academic Life Sciences," *Working Paper*, 2010.

Benjamin Balsmeier, Alireza Chavosh, Guan-Cheng Li, Gabe Fierro, Kevin Johnson, Aditya Kaulagi, Doug O'Reagan, Bill Yeh, and Lee Fleming, "Automated disambiguation of us patent grants and applications," *Working Paper*, 2015.

Bernstein, Asaf, "Household debt overhang and labor supply," *Working Paper*, November 2015.

Bernstein, Shai, "Does going public affect innovation?," *The Journal of Finance*, August 2015, *70* (4), 1365–1403.

Bogin, Alexander N., William M. Doerner, and William D. Larson, "Local house price dynamics: New indices and stylized facts," *Working Paper*, 2016.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, "How does hedge fund activism reshape corporate innovation?," *Working Paper*, 2016.

Campbell, John Y and Joao F Cocco, "How do house prices affect consumption? Evidence from micro data," *Journal of monetary Economics*, 2007, *54* (3), 591–621.

Case, Karl E, John M Quigley, Robert J Shiller et al., "Comparing wealth effects: the stock market versus the housing market," *Advances in Macroeconomics*, 2005, *5* (1).

Chaney, Thomas, David Sraer, and David Thesmar, "The collateral channel: How real estate shocks affect corporate investment," *The American Economic Review*, October 2012, *102* (6), 2381–2409.

Currie, Janet and Erdal Tekin, "Is there a link between foreclosure and health?," *American Economic Journal: Economic Policy*, 2015, *7* (1), 63–94.

Deaton, Angus, "The financial crisis and the well-being of Americans 2011 OEP Hicks Lecture," *Oxford economic papers*, 2012, *64* (1), 1–26.

Donaldson, Jason, Giorgia Piacentino, and Anjan Thakor, "Bank capital, bank credit and unemployment," *Working Paper*, 2015.

Dynan, Karen E, Jonathan Skinner, and Stephen P Zeldes, "Do the rich save more?," *Journal of Political Economy*, 2004, *112* (2), 397–444.

Eeckhoudt, Louis, Christian Gollier, and Harris Schlesinger, "Changes in background risk and risk taking behavior," *Econometrica: Journal of the Econometric Society*, 1996, pp. 683–689.

Engelberg, Joseph and Christopher A Parsons, "Worrying about the stock market: Evidence from hospital admissions," *The Journal of Finance*, 2016.

Ferreira, Daniel, Gustavo Manso, and André C. Silva, "Incentives to innovate and the decision to go public or private," *Review of Financial Studies*, January 2014, *27* (1), 256–300.

Gambetti, Elisa and Fiorella Giusberti, "The effect of anger and anxiety traits on investment decisions," *Journal of Economic Psychology*, 2012, *33* (6), 1059–1069.

Giorgetta, Cinzia, Alessandro Grecucci, Sophia Zuanon, Laura Perini, Matteo Balestrieri, Nicolao Bonini, Alan G Sanfey, and Paolo Brambilla, "Reduced risk-taking behavior as a trait feature of anxiety.," *Emotion*, 2012, *12* (6), 1373.

Guiso, Luigi and Monica Paiella, "Risk aversion, wealth, and background risk," *Journal of the European Economic association*, 2008, *6* (6), 1109–1150.

Hacker, Jacob S., Gregory A. Huber, Austin Nichols, Philipp Rehm, Mark Schlesinger, Rob Valletta, and Stuart Craig, "The economic security index: A new measure for research and policy analysis," *Review of Income and Wealth*, May 2014, *60*, S5–S32.

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, "The NBER patent citations data file: Lessons, insights and methodological tools," *Working Paper*, 2001.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg, "Market value and patent citations," *RAND Journal of Economics*, April 2005, *36* (1), 16–38.

Harhoff, Dietmar, "Firm formation and regional spillovers-evidence from germany," *Economics of Innovation and New Technology*, 1999, *8* (1-2), 27–55.

Herkenhoff, Kyle F. and Lee E. Ohanian, "Labor market dysfunction during the great recession," *Working Paper*, March 2011.

Holmstrom, Bengt, "Agency costs and innovation," *Journal of Economic Behavior & Organization*, 1989, *12* (3), 305–327.

Holmström, Bengt, "Managerial incentive problems: A dynamic perspective," *The Review of Economic Studies*, January 1999, *66* (1), 169–182.

Jaffe, Adam B. and Manuel Trajtenberg, *Patents, citations, and innovations: A window on the knowledge economy*, Cambridge and London: MIT Press, 2002.

Kimball, Miles S, "Standard risk aversion," *Econometrica: Journal of the Econometric Society*, 1993, pp. 589–611.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, "Technological innovation, resource allocation, and growth," *Working Paper*, January 2012.

Lanjouw, Jean O., Ariel Pakes, and Jonathan Putnam, "How to count patents and value intellectual property: The uses of patent renewal and application data," *Journal of Industrial Economics*, 1998, *46* (4), 405–432.

Lerner, Josh, Morten Sorensen, and Per Strömberg, "Private equity and long-run investment: The case of innovation," *Journal of Finance*, April 2011, *66* (2), 445–477.

Maner, Jon K, J Anthony Richey, Kiara Cromer, Mike Mallott, Carl W Lejuez, Thomas E Joiner, and Norman B Schmidt, "Dispositional anxiety and risk-avoidant decision-making," *Personality and Individual Differences*, 2007, *42* (4), 665–675.

Manso, Gustavo, "Motivating innovation," *Journal of Finance*, October 2011, *66* (5), 1823–1860.

_ , "Experimentation and the returns to entrepreneurship," *Review of Financial Studies*, April 2016, p. hhw019.

Mian, Atif, Kamalesh Rao, and Amir Sufi, "Household balance sheets, consumption, and the economic slump," *The Quarterly Journal of Economics*, 2013, p. qjt020.

Mulligan, Casey B., "A depressing scenario: Mortgage debt becomes unemployment insurance," *Working Paper*, November 2008.

_ , "Means-tested mortgage modification: Homes saved or income destroyed?," *Working Paper*, August 2009.

_ , "Foreclosures, enforcement, and collections under the federal mortgage modification guidelines," *Working Paper*, February 2010.

Poterba, James M, Andrew A Samwick, Andrei Shleifer, and Robert J Shiller, "Stock ownership patterns, stock market fluctuations, and consumption," *Brookings papers on economic activity*, 1995, *1995* (2), 295–372.

Pratt, John W and Richard J Zeckhauser, "Proper risk aversion," *Econometrica: Journal of the Econometric Society*, 1987, pp. 143–154.

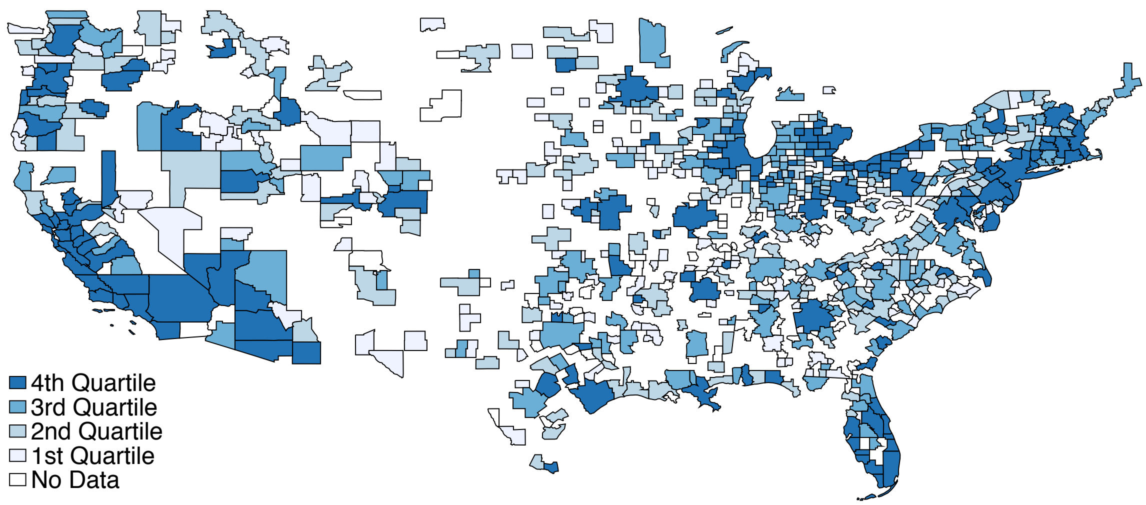
Seru, Amit, "Firm boundaries matter: Evidence from conglomerates and R&D activity," *Journal of Financial Economics*, February 2014, *111* (2), 381–405.

Trajtenberg, Manuel, Rebecca Henderson, and Adam Jaffe, "University versus corporate patents: A window on the basicness of invention," *Economics of Innovation and New Technology*, January 1997, *5* (1), 19–50.

Figure 1
House Price Variation and Inventor Location

Panel (a) of this figure shows quartiles of zip code level price variance by CBSA. Panel (b) shows quartiles of the number of inventors by CBSA, based on residence.

(a) **Local House Price Variation**



(b) **Number of Inventors by Location**

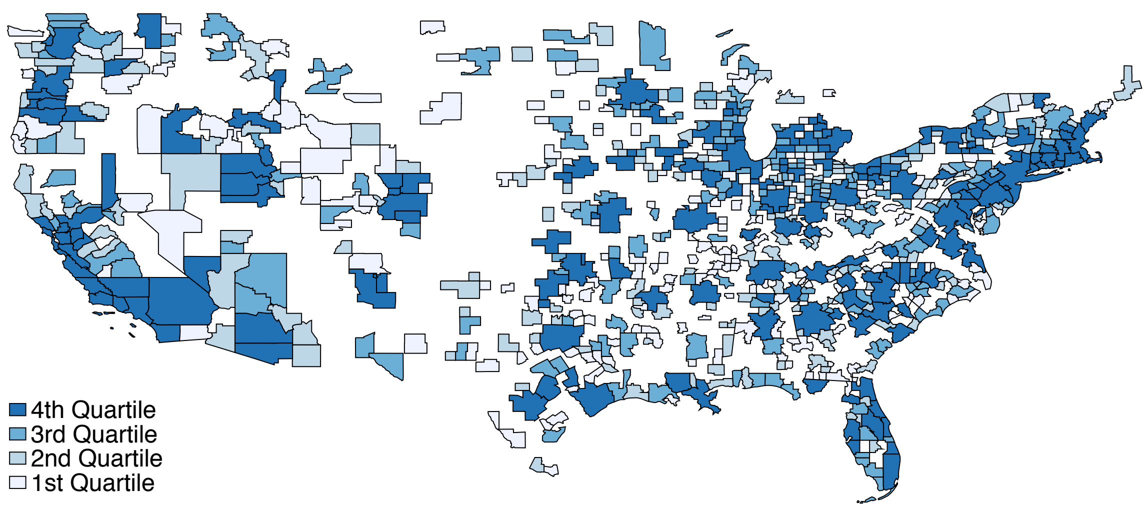
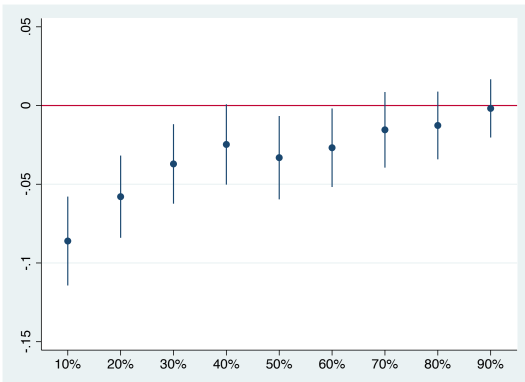


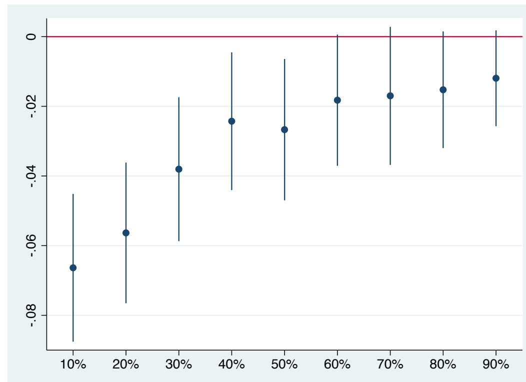
Figure 2
Treatment Intensity

This figure repeats the analysis of Tables 4-6, but separating the variable %Δ *House Price* to 10 decile dummy variables, and plots these estimates. The specification includes firm by CBSA fixed effects, and graphs report estimates of the 9 house price change deciles, relative to omitted category. The omitted category is the 10th decile (highest percentage change). Confidence intervals are at the 5% level.

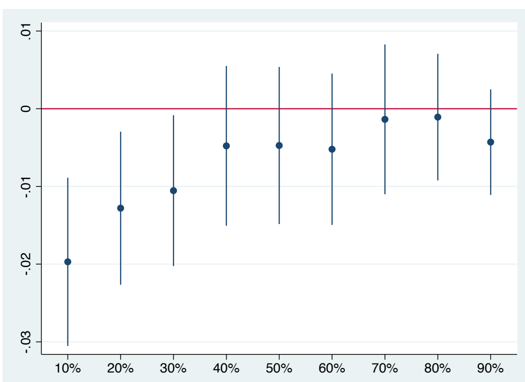
(a) **Number of Patents**



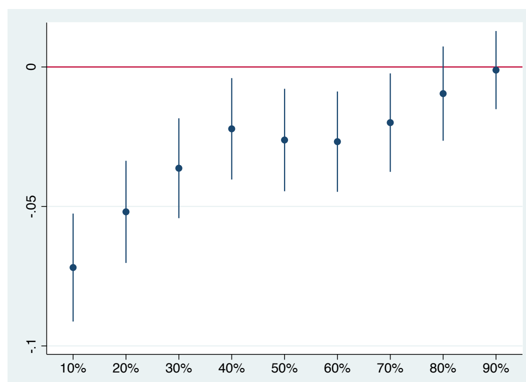
(b) **Citations per Patent**



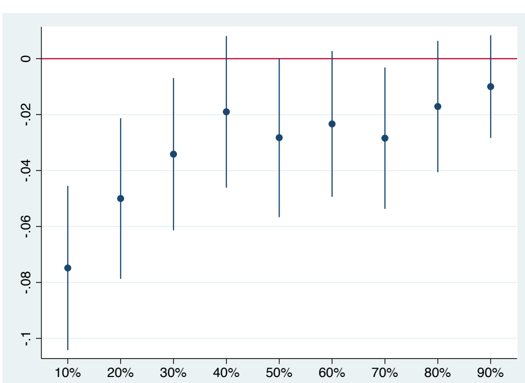
(c) **New Technology**



(d) **Exploratory Patents**



(e) **Originality**



(f) **Generality**

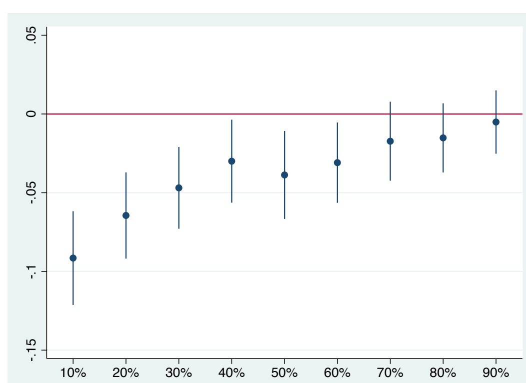


Table 1
Summary Statistics

Panel A of this table shows summary statistics for the pre-crisis and crisis periods, respectively. The pre-crisis period is defined as 2005-2007. The crisis period is defined as 2008-2012. *Number Patent* is defined as the number of eventually granted patents applied for by an inventor during the period. *Citations per paent* is the total number of citations received by a patent inventor's patents, divided *Number Patents*. A patent is *Top cited* if it was in the top 10% of all patents granted in the same year and technology class. A patent is a *New Class* patent if is in a technology class the inventor's firm has never patented in before. A patent is *Explorative* if less than 20% of the patents it cites are not existing knowledge from the point of view of the inventor's firm. Existing knowledge is defined as all patents the firm was granted in the past five years as well as all patents the firm cited in the same time frame. *Generality* is equal to one minus the Herfindahl-Hirschman Index (HHI) of forward citations across technology classes. *Origniality* is equal to one minus the HHI of backward citatations. The variable %Δ *House Price* is defined that the percent change in the inventor's zip code level price index, based in zip code of residence. The sample consists of US inventors that match to a house in CoreLogic and who are active as of onset of the crisis in 2008 (had at least one patent in the previous three years).

Panel A: Key Variables

		Pre-crisis		Crisis	
Variables	Obs	mean	sd	mean	sd
Quantity / Quality:					
Log(Number Patents)	162,076	1.15	0.589	0.645	0.798
Log(Citations Per Patent)	162,076	0.611	0.541	0.269	0.497
Log(Top Cited Patents)	162,076	0.254	0.474	0.174	0.436
Exploration / Exploitation:					
New Technology Indicator	162,076	0.262	0.44	0.0869	0.282
Log(Explorative Patents)	162,076	0.568	0.547	0.235	0.474
Log(Generality)	162,076	0.896	0.777	0.356	0.708
Log(Originality)	162,076	1.15	0.651	0.649	0.827
%Δ House Price Post	162,076	0.216	0.149	-0.163	0.128

Table 1
(Continued)

Panel B: Distribution of Inventors By Technology

NBER sub-categories	Frequency	%
Computer Hardware & Software	19,160	11.82
Communications	16,543	10.21
Drugs	13,454	8.3
Chemical (miscellaneous)	8,893	5.49
Electronic Business Methods and Software	8,085	4.99
Surgery and Medical Instruments	7,544	4.66
Semiconductor Devices	7,381	4.55
Information Storage	6,460	3.99
Power Systems	5,863	3.62
Measuring & Testing	5,426	3.35
Mechanical (miscellaneous)	4,696	2.9
Transportation	3,892	2.4
Electrical Devices	3,766	2.32
Computer Peripherials	3,420	2.11
Materials Processing and Handling	3,256	2.01
Motors, Engines and Parts	3,174	1.96
Electrical and Electronics (miscellaneous)	2,976	1.84
Resins	2,813	1.74
Nuclear, X-rays	2,497	1.54
Organic compounds	2,256	1.39

Panel C: Pre-Crisis Correlation Matrix

	Cites	Top	New	Explore	Gen	Orig
Log(Citations Per Patent)	1					
Log(Top Cited Patents)	0.6704	1				
New Technology Indicator	0.0593	0.0944	1			
Log(Explorative Patents)	0.0252	0.2252	0.334	1		
Log(Generality)	0.6157	0.7037	0.0832	0.3232	1	
Log(Originality)	0.2111	0.5564	0.0957	0.4111	0.7524	1

Panel D: Education

	Frequency	%
Bachelor	31,426	43.5
Master	13,853	19.17
PhD	19,966	27.64
MBA	6,089	8.43
J.D.	502	0.69
M.D.	411	0.57

Table 2

Quantity and Quality of Innovation

This table estimates the effect of changes in zip code level house prices on the quantity and quality of innovative output for inventors that own a house. The pre-period is defined as 2005–2007. The post-period is defined as 2008–2012. The sample consists of US inventors who are research-active as of onset of the crisis in 2008 (i.e., had at least one patent in the previous three years). All variables are as defined in Table 1. Standard errors are clustered by firm. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Number Patents Post)		Log(Citations Per Patent Post)		Log(Top Cited Patents Post)	
	(1)	(2)	(3)	(4)	(5)	(6)
%Δ House Price Post	0.195***	0.197***	0.165***	0.166***	0.121***	0.121***
	(0.0317)	(0.0316)	(0.0225)	(0.0225)	(0.0193)	(0.0192)
%Δ House Price Pre		-0.0402		0.00950		0.0131
		(-0.70)		(0.0384)		(0.0334)
Pre-crisis measure	0.702***	0.702***	0.224***	0.224***	0.380***	0.380***
	(0.0212)	(0.0213)	(0.00913)	(0.00913)	(0.0129)	(0.0129)
Firm × CBSA FE	Y	Y	Y	Y	Y	Y
R-squared	0.286	0.286	0.0514	0.0513	0.160	0.160
Observations	162,076	162,076	162,076	162,076	162,076	162,076

Table 3

Exploration

This table estimates the effect of changes in zip code level house prices on the explorativeness of innovative output for inventors that own a house. The pre-period is defined as 2005–2007. The post-period is defined as 2008–2012. The sample consists of US inventors who are research-active as of onset of the crisis in 2008 (i.e., had at least one patent in the previous three years). All variables are as defined in Table 1. Standard errors are clustered by firm. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(New Class Patents Post)		Log(Explorative Patents Post)	
	(1)	(2)	(3)	(4)
%Δ House Price Post	0.0476***	0.0480***	0.177***	0.177***
	(0.0120)	(0.0121)	(0.0211)	(0.0211)
%Δ House Price Pre		-0.0256		0.0245
		(0.0192)		(0.0383)
Pre-crisis measure	0.0779***	0.0779***	0.271***	0.271***
	(0.00385)	(0.00385)	(0.00983)	(0.00984)
Firm × CBSA FE	Y	Y	Y	Y
R-squared	0.0100	0.0101	0.0866	0.0865
Observations	162,076	162,076	162,076	162,076

Table 4
Originality and Generality

This table estimates the effect of changes in zip code level house prices on the originality and generality of innovative output for inventors that own a house. The pre-period is defined as 2005–2007. The post-period is defined as 2008–2012. The sample consists of US inventors who are research-active as of onset of the crisis in 2008 (i.e., had at least one patent in the previous three years). All variables are as defined in Table 1. Standard errors are clustered by firm. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Generality Post)		Log(Originality Post)	
	(1)	(2)	(3)	(4)
%Δ House Price Post	0.155***	0.156***	0.212***	0.213***
	(0.0315)	(0.0315)	(0.0336)	(0.0336)
%Δ House Price Pre		-0.00914		-0.0281
		(0.0484)		(0.0490)
Pre-crisis measure	0.395***	0.395***	0.639***	0.639***
	(0.0140)	(0.0140)	(0.0200)	(0.0200)
Firm × CBSA FE	Y	Y	Y	Y
R-squared	0.186	0.186	0.264	0.264
Observations	162,076	162,076	162,076	162,076

Table 5

Inventors Remaining at Same Firm

This table repeats the analysis of Tables 2–4, limiting the sample to inventors that are observed patenting at their pre-crisis firm after our estimation period ends in 2012. Standard errors are clustered by firm. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Num	(2) Cites	(3) Top	(4) New	(5) Explore	(6) Gen	(7) Orig
%Δ House Price Post	0.230***	0.226***	0.151***	0.0546***	0.175***	0.168***	0.257***
	(0.0505)	(0.0416)	(0.0326)	(0.0165)	(0.0312)	(0.0574)	(0.0519)
Pre-2008	0.636***	0.254***	0.351***	0.0851***	0.260***	0.411***	0.594***
	(0.0239)	(0.0116)	(0.0134)	(0.00549)	(0.0118)	(0.0167)	(0.0224)
Firm × CBSA FE	Y	Y	Y	Y	Y	Y	Y
R-squared	0.297	0.0594	0.167	0.0125	0.0875	0.204	0.280
Observations	77,942	77,942	77,942	77,942	77,942	77,942	77,942

Table 6
Alternative Specifications

This table repeats the analysis of Tables 2–4 interacting firm by CBSA fixed effects with various other 2007 characteristics. Only the main coefficient on *%Δ House Price Post* is shown, but other controls remain the same. We define an inventor's *Tech Class* to be the modal 3-digit class of the inventor's patents in the pre-period. We define *Experience* as the number of years, as of 2007, since the inventor's first patent. We calculate age as the number of years, as of 2007, since the inventor's first degree, plus 21. We define education as a series of indicator variables representing the inventor's highest degree obtained. We define an inventor to have a senior position if one of the following words appears in the position title: manager, director, president, VP, chief, CEO, CTO, management, executive, principal, partner, chairman, manager, head, or chair.
Standard errors are clustered by firm. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Specification	(1) Num	(2) Cites	(3) Top	(4) New	(5) Explore	(6) Gen	(7) Orig
Panel A: Full Sample							
(1) Firm X CBSA FE	0.196***	0.166***	0.121***	0.0477***	0.177***	0.156***	0.213***
	(0.0317)	(0.0225)	(0.0193)	(0.0121)	(0.0211)	(0.0315)	(0.0336)
(2) Firm X CBSA X Tech Class FE	0.159***	0.133***	0.114***	0.0333**	0.157***	0.132***	0.173***
	(0.0395)	(0.0278)	(0.0249)	(0.0134)	(0.0284)	(0.0407)	(0.0416)
(3) Firm X CBSA X Experience FE	0.199***	0.127***	0.101***	0.0522***	0.155***	0.136***	0.211***
	(0.0345)	(0.0240)	(0.0205)	(0.0128)	(0.0238)	(0.0346)	(0.0363)
(4) Firm X CBSA X Neighborhood Income FE	0.175***	0.132***	0.0874***	0.0443***	0.169***	0.118***	0.184***
	(0.0421)	(0.0318)	(0.0270)	(0.0157)	(0.0294)	(0.0435)	(0.0444)
(5) Firm X CBSA X Square Footage FE	0.190***	0.154***	0.107***	0.0417***	0.165***	0.137***	0.198***
	(0.0337)	(0.0254)	(0.0215)	(0.0133)	(0.0240)	(0.0356)	(0.0363)
(6) Firm X CBSA X Urban Neighborhood	0.215***	0.183***	0.128***	0.0600***	0.190***	0.169***	0.227***
	(0.0336)	(0.0269)	(0.0222)	(0.0137)	(0.0244)	(0.0367)	(0.0360)
(7) Firm X CBSA X Family Neighborhood	0.182***	0.162***	0.113***	0.0555***	0.172***	0.133***	0.181***
	(0.0425)	(0.0309)	(0.0257)	(0.0151)	(0.0307)	(0.0445)	(0.0435)
Panel B: LinkedIn Sample							
(8) Firm X CBSA FE	0.239***	0.227***	0.148***	0.0378**	0.217***	0.175***	0.259***
	(0.0486)	(0.0372)	(0.0311)	(0.0182)	(0.0342)	(0.0502)	(0.0503)
(9) Firm X CBSA X Age FE	0.284***	0.229***	0.153***	0.0304	0.283***	0.209***	0.310***
	(0.0761)	(0.0596)	(0.0549)	(0.0277)	(0.0510)	(0.0792)	(0.0794)
(10) Firm X CBSA X Education FE	0.188***	0.176***	0.0977***	0.00299	0.164***	0.115**	0.214***
	(0.0574)	(0.0425)	(0.0364)	(0.0203)	(0.0466)	(0.0698)	(0.0671)
(11) Firm X CBSA X Senior Position FE	0.260***	0.228***	0.155***	0.0377**	0.240***	0.183***	0.279***
	(0.0522)	(0.0395)	(0.0328)	(0.0184)	(0.0355)	(0.0535)	(0.0542)

Table 7
Labor Market

This table repeats the analysis of Tables 2–4, now allowing *%Δ House Price Post* to interact a *Popular Technology* indicator. To define the *Popular Technology* indicator we classify inventors to a technology class based on the modal technology class they patented in during the five years before the crisis. An inventor is consider to specialize in a popular technology if the inventor's technology class is in the top quartile in terms of number of total inventors. Standard errors are clustered by firm. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Num	(2) Cites	(3) Top	(4) New	(5) Explore	(6) Gen	(7) Orig
%Δ House Price Post ×	-0.117**	-0.0846***	-0.0565**	0.002	-0.0422	-0.117***	-0.138***
Popular Technology	(0.0477)	(0.0300)	(0.0247)	(0.0141)	(0.0288)	(0.0433)	(0.0493)
Pre-2008	0.701***	0.229***	0.379***	0.0790***	0.266***	0.394***	0.635***
	(0.0189)	(0.0083)	(0.0112)	(0.0034)	(0.0087)	(0.0124)	(0.0177)
Zip Code FE	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
R-squared	0.466	0.316	0.372	0.329	0.283	0.400	0.454
Observations	148,655	148,655	148,655	148,655	148,655	148,655	148,655

Table 8
House Ownership Duration

This table repeats the analysis of Tables 2–4, now allowing *%Δ House Price Post* to interact a *Purchase before 2005* indicator equal to one if the inventor's house was purchased prior to 2005. Standard errors are clustered by firm. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Num	(2) Cites	(3) Top	(4) New	(5) Explore	(6) Gen	(7) Orig
%Δ House Price Post ×	-0.114***	-0.0809***	-0.0655***	0.00104	-0.0384	-0.125***	-0.0954**
Purchase before 2005	(0.0440)	(0.0303)	(0.0254)	(0.0165)	(0.0306)	(0.0415)	(0.0442)
Pre-2008	0.706***	0.228***	0.380***	0.0795***	0.267***	0.396***	0.640***
	(0.0187)	(0.00832)	(0.0112)	(0.00340)	(0.00865)	(0.0124)	(0.0177)
Zip Code FE	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
R-squared	0.473	0.317	0.374	0.329	0.285	0.403	0.460
Observations	148,655	148,655	148,655	148,655	148,655	148,655	148,655

Table 9
Housing Prices Effects in 2002

This table repeats the analysis of Tables 2–4, but estimates the effect of changes in zip code level house prices on innovative output for an earlier period. The pre-period is defined as 1999–2001. The post-period is defined as 2002–2006. The sample consists of US inventors who are research-active as of 2002 (i.e., had at least one patent in the previous three years). All variables are as defined in Table 1. Standard errors are clustered by firm. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Num	(2) Cites	(3) Top	(4) New	(5) Explore	(6) Gen	(7) Orig
%Δ House Price Post	-0.019	0.0164	-0.00316	-0.0136	-0.0174	-0.0032	-0.0213
	(0.0451)	(0.0238)	(0.0222)	(0.0132)	(0.0273)	(0.0453)	(0.0470)
Pre-2002	0.410***	0.155***	0.216***	0.0361***	0.148***	0.328***	0.395***
	(0.0221)	(0.00695)	(0.0103)	(0.00348)	(0.00992)	(0.0173)	(0.0203)
Firm $\times$ CBSA FE	Y	Y	Y	Y	Y	Y	Y
R-squared	0.075	0.027	0.053	0.002	0.022	0.071	0.076
Observations	161,892	161,892	161,892	161,892	161,892	161,892	161,892

APPENDIX

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A Career Concerns Model

In this section we begin with a highly stylized, simple model to explore the connection between risk-taking behavior within a firm and house prices. The model is a variant of the Holmström (1999) work on incentive provision through career concerns. We begin by outlining the model's basic structure and key intuition. In the model, firms would like their high quality inventors to pursue risky, yet positive NPV, exploratory innovations instead of pursuing safe exploitation of the firm's existing knowledge base. However, firms cannot observe the exploration or exploitation choice made by inventors. Instead, they only see the output that inventors produce. Moreover, inventors have varying levels of ability and only the most able can successfully undertake exploratory innovation. Likewise, the lowest quality inventors fail at both exploration and exploitation. Crucially, firms cannot observe inventor type ex-ante. The key tradeoff of the model arises from the interplay of hidden action, asymmetric information, and the fact that successful exploration is not guaranteed. Successful exploration will signal that an inventor is of high quality and thus increase her market

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wage, but unsuccessful exploration, which occurs with some positive probability, will lead the market to falsely believe that the inventor is of low quality. This tradeoff determines whether a high quality inventor optimally chooses exploration or exploitation.

The model shows that fluctuations in housing net worth interacts with the inventor's tolerance to failure and the decision to pursue exploration since exploration can result with lower wages or job loss in the case of a failure. The model's predictions on the direction of the effect are ambiguous, however. For instance, if default costs are high, inventors with lower priced homes may pursue exploitation since they worry that losing one's job due to a failed exploration would force them into costly foreclosure. Conversely, if default costs are low, inventors with low prospects of profitable house price recovery may pursue riskier projects since there is much lesser need to pursue safe projects that will ensure job security to maintain mortgage payments. We now turn to formally describing the model and presenting these results.

A.1 Basic Setup

Risk-neutral inventors operate in a competitive labor market. There are three types of inventors, high quality (H) , medium quality (M), and low quality (L). Inventors know whether or not they are of high quality and this information is private. However, conditional on knowing that they are not high quality, inventors do not know if they are of medium quality or low quality.[1] The fraction of inventors that are low quality is given by ϕ_L, the fraction that are medium quality by ϕ_M, and the fraction that are high quality by ϕ_H. As in Holmström (1999), we rule out the existence of contracts contingent on realized output.

There are three dates, which we label $t = -1, 0, 1, 2$. Inventors are born at date $t = -1$. At date 0, inventors are hired and paid a competitive fixed wage w_0 equal to their expected marginal output. After receiving their fixed wage, inventors then decide to pursue a safe, exploitative task or a risky, exploratory task. We denote the binary choice $a = \{X, E\}$, with $a = X$ denoting the exploitative task and $a = E$ denoting the exploratory task. Importantly, the task choice is not

[1] This assumption is made for tractability reasons and is not essential to the analysis which follows.

observed by the market. If successful, the exploitative task produces marginal output y_X. The exploratory task produces marginal output $y_E > y_X$, if successful. Low quality inventors always fail at both tasks. Medium quality inventors will always succeed at the exploitative task, but always fail at the exploratory task. High quality inventors always succeed at the exploitative task and may successfully complete the exploratory task with probability α. We assume that $\alpha y_E > y_X$ so that the firm would always like its high quality inventors to pursue exploratory tasks. We let $\Delta = y_X/\alpha y_E < 1$. The lower Δ, the more attractive is the exploratory task. The key frictions in the model are that firms do not observe worker type and do not observe the task chosen by the worker. Firms only observe the output produced by the worker at the end of date $t = 0$. Thus, in the event that a high quality inventor fails at the exploratory task, the market may falsely believe the inventor to of low quality.

At time $t = 1$, the market updates its beliefs regarding the type of an inventor based on the date 0 output realizations. Inventors are again hired, paid a fixed wage, and then choose a task $a = \{X, E\}$. The fixed wages inventors receive at the beginning of period 1 reflects the market's beliefs of inventor type. Specifically, inventors are paid a wage $w_{1,E}$ if the output realization in the previous period was y_E, a wage $w_{1,X}$ if the output realization was y_X, and a wage $w_{1,F}$ if the output realization was zero. At date $t = 2$, workers consume their net worth, and then die. There is no intermediate consumption. No labor occurs at date $t = 2$. For simplicity, we assume that there is no time discounting and that the real interest rate is equal to zero.

The solution concept is Perfect Bayesian Equilibrium. This requires that the market's updating rule is consistent with equilibrium actions. Note that all workers who know that they are not high quality will choose the exploitative action, so our focus is on the task choice of high quality inventors. We furthermore note that the action choice of high quality inventors in period 1 is indeterminate. We therefore suppose that inventors choose the same action as in period 0.[2] This directly implies that the updated competitive wages are $w_{1,E} = \alpha y_E$ and $w_{1,X} = y_X$. If the market observes y_E at

[2] We assume that there is a small effort cost reduction in pursuing the same task chosen in date 0. This makes choosing the same task optimal.

the end of period 0, it knows the inventor is of high quality. The inventor will again choose the exploratory task, so the expected marginal output is αy_E. If the market observes y_X at the end of period 0, the market knows the inventor is not of low type. Since the inventor will choose the exploitative task in period 1, the expected marginal output is y_X. The following theorem provides parameter restrictions such that high quality inventors choose the exploratory task. If the success probably of exploratory task is sufficiently high such that $\alpha > \Delta$, then the unique Perfect Bayesian Equilibrium is one in which all high quality inventors choose the exploratory task in period 0. Inventors seek to maximize $w_0 + E\left[w_1^i\right]$. Suppose that there exists an equilibrium in which high quality inventors choose the exploitative task at date 0. Then they receive the wage $w_{1,X} = y_X$ in period 1. Suppose a high quality inventor deviates to the exploratory task in period 0. If the task fails, then the inventor will receive a wage of zero in period 1 by Bayesian updating. That is, since in the conjectured equilibrium all high quality inventors choose the exploitative task, a failure will be interpreted by the market as a sure signal that the inventor is low quality. If the task succeeds, then the wage will be αy_E in period 1 since only high quality inventors can produce output y_E. Thus, the expected wage from a deviation is $\alpha^2 y_E$. The deviation will be not be profitable if $y_X \geq \alpha^2 y_E$, or, equivalently, if $\alpha \geq \Delta$. This violates the assumption, so the conjectured equilibrium does not exist.

Conversely, suppose that all inventors choose the exploratory task in period 0. If the exploration succeeds, the inventor receives the wage αy_E. By Bayes' rule, inventors receive the wage $\frac{(1-\alpha)\phi_H}{(1-\alpha)\phi_H+\phi_L}\alpha y_E$ if the task fails. The expected date 1 wage is therefore:

$$\alpha^2 y_E + \frac{(1-\alpha)^2\phi_H}{(1-\alpha)\phi_H + \phi_L}\alpha y_E.$$

Since $\alpha > \Delta$, a deviation to exploitation, will guarantees a date 1 wage of y_X, is not profitable. Thus, exploration by high quality inventors constitutes a Perfect Bayesian Equilibrium. Intuitively, incentive provision for exploration is provided through the desire of high quality inventors to signal their type to the market and thus increase their wage. High quality inventors trade-off this potential increase in their wage against the risk that the exploration fails and the market then updates in falsely believing that the inventor is of low quality, thereby decreasing the wage. For a sufficiently high probability of success, the expected gain will always outweigh the expected cost, such that exploration is the unique equilibrium.

A.2 Introducing Housing Net Worth Shocks

To this basic setup, we add housing market concerns. We now suppose all inventors are born at $t = -1$ with a house valued at price p_{-1}, a mortgage with balance $L < p_{-1}$, and a fixed principal payment π due at time $t = 1$. At date 0, there is a housing crisis and inventors receive shocks to the value of their home. A fraction ω of inventors receive a shock such that their house price becomes $p_0^h > L$, while a fraction $1 - \omega$ receive a more severe shock such that their house price becomes$p_0^l < L/(1+g)$ where $g > 0$. House prices are expected to appreciate by g percent following the crisis, but the timing of recovery is uncertain. With probability $1 - \gamma$, house prices appreciate at date 1, so that the house of an inventor increases in value to $p_1^i = (1+g)\, p_0^i$. Otherwise, with probability γ, house prices remain flat in period 1 and the appreciation occurs at date 2, such that $p_1^i = p_0^i$ and $p_2^i = (1+g)\, p_0^i$. If the sum of an inventor's wages in periods 0 and 1 $w_0 + w_1^i$ is less than π, then the inventor must either sell the house $\left(p_1^i \geq L\right)$ or default $\left(p_1^i < L\right)$. Inventors incur an additional default cost $D \geq 0$ in the event of default. Inventors therefore choose the task that maximizes their date 2 expected net worth:

$$
\begin{aligned}
W_{2,i} = {} & E\left[w_0 + w_1^i + \left(p_2^i - L\right)^+ | w_0 + w_1^i \geq \pi\right] P\left(w_0 + w_1^i \geq \pi\right) \\
& + E\left[w_0 + w_1^i + \left(p_1^i - L\right)^+ | w_0 + w_1^i < \pi\right] P\left(w_0 + w_1^i < \pi\right) \\
& - DP\left(w_0 + w_1^i < \pi,\ p_1^i < L\right)
\end{aligned}
$$

If wages remain sufficiently high, as is the case in the first term, the inventor is able to hold onto the house until the final period. The inventor then consumes the sum of her wages as well as any equity she has built up in the house. If wages fall below the required mortgage payment in period

1, as illustrated in the second term, the worker consumes the sum of her wages and any equity in the house at date $t = 1$, since she must sell the house early. The inventor is forced to default at time $t = 1$ if wages fall below mortgage payment *and* house prices are below the mortgage balance L. In that case, the inventor incurs the additional default cost D.

The following two lemmas provide parameter restrictions which ensure that the housing related concerns have an impact. The first imposes that the inventor may be forced to sell the house if the exploratory project fails, and the second implies that the inventor can avoid selling the house if pursing the safe, exploitative, project. Suppose $\phi_M y_X + \phi_H \alpha y_E + \frac{(1-\alpha)\phi_H}{(1-\alpha)\phi_H + \phi_L} \alpha y_E < \pi$. Then, in any equilibrium, the inventor will be forced to either sell or default if the exploratory task does not succeed. Date 0 and date 1 wages are maximized in an equilibrium in which all high quality inventors choose the exploratory task. The expression $\phi_M y_X + \phi_H \alpha y_E$, equal to the expected date 0 marginal output, and provides the competitive date 0 wages in such an equilibrium. The expression $\frac{(1-\alpha)\phi_H}{(1-\alpha)\phi_H + \phi_L}$ is the posterior probability that an inventor is high quality in such an equilibrium, so that $\frac{(1-\alpha)\phi_H}{(1-\alpha)\phi_H + \phi_L} \alpha y_E$ are date 1 wages in the event that no output is observed. Thus, this condition implies that even in an equilibrium in which wages are maximized, a failure will result in the inventor having insufficient funds to cover the date 1 mortgage payment. Suppose $(\phi_M + \phi_H + 1)\, y_X \geq \pi$. Then, in any equilibrium, a high quality inventor can avoid early liquidation and default by choosing exploitation. The logic is similar to that above. Wages are minimized in an equilibrium in which all high quality inventors choose the exploitative action. The date 0 marginal output $(\phi_M + \phi_H)\, y_X$ provides the date 0 competitive wages in such an equilibrium. High quality inventors can guarantee the wage y_X in period 1 by choosing the exploitative action. Thus total wages from exploitation are therefore given by $(\phi_M + \phi_H + 1)\, y_X$ in the worst-case equilibrium. Given the parameter restriction, these wages are sufficiently high to cover the required mortgage payment and thus avoid forced sale of the house.

We now turn to investigating the impact of housing related concerns on equilibrium exploration by high quality inventors. We begin by supposing $\gamma > 0$ and $D = 0$. That is, default costs are zero and thus the key concern facing inventors vis a vis their property is being forced to liquidate at an inopportune time, which may prevent taking advantage of potential recovery of housing prices. We have the following result: Suppose $\alpha > \Delta$. For $\gamma g p_0^h > 0$ sufficiently large, the unique Perfect Bayesian Equilibrium is one in which high quality inventors with low housing prices $\left(p_0^i = p_0^l\right)$ pursue exploration and those with higher housing prices $\left(p_0^i = p_0^h\right)$ pursue exploitation. Consider the incentives of high quality inventors whose house is initially valued at $p_0^l < L/\left(1+g\right)$. Their housing equity is already equal to zero and will continue to be zero at date 2. Therefore, since default is not costly, these investors are not troubled by the prospect of being forced to sell or default at date 1. Losing the house at date 1 and missing out on future house priuce appreciation has no impact on their date 2 net worth. It then follows that in any equilibrium, these investors always pursue exploration. The logic is exactly the same as in the discussion following Theorem 1. The worst possible expected wage from exploration is $\alpha^2 y_E$, while the guaranteed wage from exploitation is y_X. Since $\alpha > \Delta$, exploration will always be more profitable.

On the other hand, note that$\gamma g p_0^h$ is the probability-weighted cost of being forced to sell early for those inventors with higher house prices $\left(p_0^i = p_0^h\right)$ at date 0. Since $p_0^h > L$, these investers would benefit from the expected housing recovery. If they are forced to sell at date 1, however, and recovery occurs at date 2, then they would miss out on the expected price appreciation. If the cost $\gamma g p_0^h$ is sufficiently large such that:

$$\alpha^2 y_E + \frac{\left(1-\alpha\right)^2 \phi_H}{\left(1-\alpha\right)\phi_H + \phi_L}\alpha y_E - \left(1-\alpha\right)\gamma g p_0^h < y_X,$$

Recall that:

$$\frac{\left(1-\alpha\right)\phi_H}{\left(1-\alpha\right)\phi_H + \phi_L}\alpha y_E$$

is the maximal possible period 1 wage in the event of zero output. So the first two terms in the LHS of the equation provide the maximal possible expected wage from exploration, while the third term is the expected housing net worth loss an inventor incurs,$\gamma g p_0^h$, due to early liquidation, multiplied by the probability $(1-\alpha)$ that exploration fails and she is forced to sell the house. High quality inventors can guarantee a wage of y_X by choose exploitation. Thus, by the inequality above, exploitation is always more profitable than exploration for $\gamma g p_0^h$ sufficiently large. The key takeaway is that in the presence of an expected recovery, those with higher house prices and therefore more to lose may be less willing to take risk than inventors with less housing net worth . These results can flip though if default itself is costly, as the following theorem illustrates. Suppose $\alpha > \Delta$. For $\gamma g p_0^h > 0$ sufficiently small and $D > 0$ sufficiently large, the unique Perfect Bayesian Equilibrium is one in which high quality inventors with low housing prices $\left(p_0^i = p_0^l\right)$ pursue exploitation and those with high housing prices $\left(p_0^i = p_0^h\right)$ pursue exploration. Consider the case in which the expected cost of early liquidation$\gamma g p_0^h > 0$ is sufficiently small and $D > 0$ sufficiently large such that:

$$\alpha^2 y_E - (1-\alpha)\,\gamma g p_0^h > y_X$$

$$\alpha^2 y_E + \frac{(1-\alpha)^2\,\phi_H}{(1-\alpha)\,\phi_H + \phi_L}\alpha y_E - (1-\alpha)\,\delta\gamma D < y_{X.}$$

The worst possible equilibrium date 1 wage in the event exploration fails is equal to zero. Thus $\alpha^2 y_E - (1-\alpha)\,\gamma g p_0^h$ is the worst possible expected value from exploration for inventors with positive housing equity at date 0. The first inequality, along with the parameter restriction $\alpha > \Delta$, thus guarantees that exploration is always more profitable the exploitation for high quality inventors with $p_0^i = p_0^h$. On the other hand, inventors with $p_0^i = p_0^l$ will be forced to default in the event exploration fails. By the same logic as in the the previous theorem, the second inequality guarantees that exploitation is always more profitable than exploration for these inventors. Therefore, the unique equilibrium is one in which inventors with $p_0^i = p_0^h$ choose exploration and inventors with $p_0^i = p_0^l$ choose exploitation. Intuitively, when early liquidation concerns are relatively small but default itself is costly, it is those inventors with little positive housing equity (and thus close to default) who are unwilling to undertake risky innovation. The model therefore delivers ambiguous results regarding the interaction of housing net worth with innovation by employed inventors. On the one hand, it might be that employees pursue safer projects if they worry that losing their job would force them into costly foreclosure. But on the other hand, significant price declines may lead employees to pursue riskier projects if they no longer believe in a profitable recovery of housing prices. In that case, safe projects that ensure job security to maintain mortgage payments may no be longer needed.