Does Economic Insecurity Affect Employee Innovation?

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Abstract

Do household wealth shocks affect employee output? We examine this question through the lens of technological innovation, by comparing employees that worked at the same firm and lived in the same metropolitan area, but experienced different housing wealth declines during the 2008 crisis. Following a housing wealth shock, employees are less likely to successfully pursue innovative projects, particularly ones that are high impact, exploratory, or complex in nature. Consistent with employee concerns about financial distress, the effects are more pronounced among those who had little equity in their house before the crisis and among those with fewer outside labor market opportunities. In addition, run-ups in housing prices before the crisis did not affect employee innovation. The results highlight a "bottom-up" view of innovation, in which individual employees influence the type and nature of innovation produced within the firm.

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1 Introduction

How does employee output respond to large shocks to household wealth? Over the past 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 consequences of such household wealth shocks on household choices such as consumption, saving, and retirement 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; Goda et al., 2011; McFall, 2011; Mian et al., 2013). However, household wealth fluctuations may have a bearing on firms as well. Yet, the effects of such shocks on employees' work output, and by extension, the output of firms, remain largely unstudied. We attempt to fill this gap by investigating whether economic insecurity affects employee output through the lens of technological innovation, a critical driver of economic growth (Solow, 1957).

Economists have long argued that the rate and direction of technological change should be understood as the outcome of firms' profit-driven investment in innovation (Schmookler (1962); Griliches (1957); Nelson (1959); Arrow (1962)). Indeed, the literature has focused almost entirely on market-level and firm-level factors such as industry competition, firm's investment horizon, institutional ownership, and organizational structure.[1] This view, however, neglects the incentives and motives of inventors within firms. These individual employees are those who must undertake such innovative, complex projects, that require significant exploration and may fail (Manso (2011)). This raises the question of whether employees' personal financial situations might impact both their willingness and ability to pursue such innovations.

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 and widespread shock that led to increased economic insecurity. Specifically, we investigate whether declines in housing wealth experienced by individual employees affected their innovative output in the firm.

[1] Few recent examples include Aghion et al. (2005, 2013); Bernstein (2015b); Budish et al. (2015); Lerner et al. (2011); Seru (2014)

The effect that housing shocks may have on employee output, and innovative output in particular, is theoretically ambiguous. First, it may be that employees are well-monitored and have little ability to change the amount of effort they exert. They may also have little control over which projects they work on, as this may be determined by higher-level managers. Under these conditions, one might expect financial shocks to individual employees to have no effect on either the quantity or nature of their innovative output.

Absent these conditions, however, it is possible that negative housing shocks could affect employee productivity through concerns about mortgage-driven financial distress. The literature on mortgage default emphasizes that default patterns tends to follow a "double-trigger" model. That is, default occurs when when individuals have negative home equity coupled with a significant negative liquidity shock, such as loss of employement (e.g., Foote et al., 2008, 2010). Thus, borrowers who are closer to being underwater are more vulnerable to being forced into default, which likely carries a variety of financial and non-financial costs.[2] It is unclear whether concerns about forced default would lead employees to become more or less productive. On the one hand, such concerns may lead to stress and anxiety, making employees less productive. On the other hand, these concerns may lead to an increased desire for job-security, making employees more productive.[3]

Given these considerations, how housing shocks affect employee output is ultimately an empirical question. The first challenge in answering this question is obtaining individual-level data on employee output. We address this by focusing on innovative output, as measured by patents. Patents credit individual employees as inventors, even when the patent is assigned to a firm. Therefore, we are able to observe innovation output at the individual level. Moreover, we observe not

[2]Mortgage default likely carries both direct financial costs from legal and moving fees as well as non-financial costs due to utility loss from relocating to a less desirable house, neighborhood, or school district. It also may carry indirect costs stemming from reputational damage with potential creditors, employers, landloards, insurance companies, and others that screen based on credit reports. In addition, default may carry significant psycological costs due to associated stress and anxiety.

[3]In addition, if pursuing more innovative projects is riskier for employees due to a higher probability of failure, housing shocks may have additional ambiguous effects. First, negative housing shocks may lead employees to become more risk-averse due to declines in wealth, which may lead them to pursue less innovative projects(Guiso and Paiella, 2008). Second, those concerned about forced default might strategically try to enhance their job security by pursuing less innovative projects (Sauermann and Cohen, 2010). Finally, if forced default is not very costly, employees who have negative equity and believe price recovery is unlikely may pursue more innovative projects, since the importance of maintaining job security to make mortgage payments is relatively low.

only the quantity and quality of employees' innovative output, we can also characterize this output in a very detailed manner using measures that capture whether employees engage with novel and exploratory technologies (e.g., Benjamin Balsmeier et al., 2015; Chen Lin et al., 2016). We complement the patent data with data from LinkedIn, which includes employee characteristics such as age, education, experience, tenure, and job title. Finally, the patent data also record inventors' city of residence and, in many cases, their full residential address. This allows us to link these data with deed records from CoreLogic. From the deed records we can identify employees that are home owners, observe the exact location of the house, and other characteristics such as purchase price, square-footage, and number of bedrooms. These data allow us to exploit localized housing price shocks as well as to control for detailed employee and house characteristics, and link it with employee innovation.

The second challenge is identifying the causal impact of housing shocks on employee output. Clearly, the location of an employee'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 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 had worse innovative opportunities during this time period for reasons unrelated to the decline in local house prices. To address these issues, our analysis compares only employees working at the *same* firm—who are therefore similarly affected by firm-level changes in demand, borrowing capacity, or innovative opportunities—but who are exposed to different house price shocks.

Additional concerns, however, 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 within the same firm, those who live in more crisis-affected areas may work in divisions with bigger changes in innovative opportunities. To address this concern, we further restrict our analysis to compare only employees who work at the same firm and also live in the same metropolitan area, as defined by a census Core Based Statistical Area (CBSA). For most firms, this implies that we are comparing employees working at the same local office.[4] Despite the fact that we compare employees living in the same metropolitan area, there remains substantial variation in the house price shocks that they experience, because we exploit house price shocks at the zip code level.

Using this empirical approach, we find that negative shocks to housing wealth during the crisis significantly affect employee innovation. We find that employees who experience a negative housing wealth shock appear to produce fewer patents and patents of lower quality based on citations. Interestingly, such employees are also less likely to patent in technologies that are new to their firm, and, more generally, their patents are less likely to draw upon information from outside their firm's existing knowledge base. Finally, these employees also produce narrower innovations, combining information from fewer disparate fields. These effects are strongest among those employees who suffer the largest housing price declines. Overall, the evidence suggests that following a housing wealth shock, employees are less likely to successfully pursue innovative projects, particularly ones that are high impact, exploratory, or complex. The results are inconsistent with the null hypothesis under which employees cannot adjust the nature of their innovative projects, and also inconsistent with the hypothesis that housing wealth shocks lead employees to become more innovative.

We conduct additional tests to verify the robustness of the results, by exploring even a narrower comparison of employees within the same firms and metropolitan areas. For example, we compare the response of employees who are at a similar age, or with a similar level of education. We compare the response of employees that specialize in similar technologies at the onset of the crisis. We compare the response of employees that select to live in a similar type of neighborhood or at a similar type of house.[5] In all these cases, our key results remain remarkably stable. Employees that experienced a large decline in housing wealth pursued less exploratory and innovative projects. Therefore, the baseline results are unlikely to be explained by sorting of certain types of employees in the firm into more crisis-affected zip codes within a metropolitan area. In fact, in the heterogeneous

[4]This also implies that these employees reside within the same labor market, and thus are likely facing similar work opportunities outside of their firm.

[5]To be more specific, we compare employees that choose to live in neighrbohoods with similar characteristics such as income, ratio of urban and rural population, and family orientation, measured by average number of kids per family. We also compare employees that choose to live in a similar house, based on the square footage of the house.

analysis described below, we can even include zip code fixed effects, thus controlling for employee selection into zip-codes. Our results results remain unchanged.

The finding that household shocks can affect employee innovation has interesting implications for our understanding of how innovation is generated within firms. A large literature on the determinants of firm innovation, originated by Schmookler (1962); Griliches (1957); Nelson (1959) and Arrow (1962), highlights a "top-down" view, in which firms' profit-driven objectives determine innovation policy, which is then implemented by employees. The literature, thus, has focused on firm-level and market-level factors to explain variation in innovation levels across firms (see e.g., Harhoff, 1999; Aghion et al., 2005; Lerner et al., 2011; Manso, 2011; Aghion et al., 2013; Ferreira et al., 2014; Seru, 2014; and Bernstein, 2015b) . In contrast, our results suggest that innovation within firms can follow a "bottom-up" process as well, in in which individual employees have sufficient autonomy to affect the type and nature of innovation produced within the firm. To our knowledge, this paper is the first to directly study how household level shocks affect firm innovation.

We continue by exploring various channels through which our results may operate. In particular, we try to distinguish the effects of wealth losees on employee risk preferences from employee concerns about financial distress stemming from costly mortgage default. Under the wealth effects channel, declines in housing wealth may increase risk aversion, due to employee preferences, and thus lead to a decline in innovative output. Under this logic, we would also expect that increases in wealth translate into greater risk taking. Hence, we repeat our analysis but during the boom period, in the years leading up to the crisis, between 2002 and 2007. Here we find no statistically significant relation between housing wealth and innovation during that time period. This suggests an asymmetry between housing wealth increases and decreases. Such an asymmetry is inconsistent with a simple wealth effects story in which risk aversion decreases with wealth gains and increases with wealth losses.

Instead, our results are consistent with employees' concerns about financial distress arising from costly mortgage default. Consistent with the double-trigger model of default, we find that employees who are likely to have less equity in the house at the onset of the crisis, were more sensitive to the shock, and experienced a larger decline in innovation.[6] Moreover, we find that employees with more outside labor market opportunities, due to their field of expertise, and thus are less likely to be unemployed, were less sensitive as well to declines in housing wealth. Hence, both higher equity at the house, and higher labor market opportunities seem to lower the sensitivity of empoyee output to declines in housing wealth, as is suggested by the "double-trigger" model. These results may also be of interest to policymakers concerned with macroprudential policy related to the housing market, such as the appropriate level of Loan-to-value requirements.

This paper relates to several strands of the literature. Beyond the innovation literature, mentioned above, 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 different. We control for the collateral channel at the firm level with firm fixed effects and instead illustrate that house price movements also affect employee incentives and innovative output within the firm.

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. Charles et al. (2015)studies the impact of the housing boom and bust on college enrollment and attainment. Conversely, our focus is on individuals who are already employed and the impact of household leverage on project selection and productivity within the firm.

The rest of the paper paper proceeds as follows. Section 2 describes the data. Section 3 details our empirical strategy. Section 4 presents our results. Section 5 investigates heterogeneity and Section 6 discusses potential channels. Section 7 concludes.

[6]Again, these results are inconsistent with the wealth effects channel since those who had more equity, if anything, experienced larger wealth losses when house prices declined, than those who hit the zero equity bound.

2 Data

2.1 Data Sources and Sample Selection

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 firm 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 firms. In order to identify inventors and firms 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 firms, and patent classifications to create an inventor identifier. While Benjamin Balsmeier et al. also provide a firm 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 firm 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.[7]

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

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

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 52% 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 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 individuals who 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.[8]

Together, we construct an annual employee-level panel. In each year we observe an employee's innovative output along with the location of the employee'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 employee characteristics during years in which the employee has zero patents. For example, if an employee changes firms we can only observe the change the next time the employee patents. In order to ensure that we are studying employees that are still active and that our information about them is not too stale, we limit our sample to individuals who, during the three years preceding the 2008 financial crisis, applied for at least one patent that was assigned to a firm. There are 321,837 such individuals in the USPTO data. Of these, we are able to identify a house in CoreLogic for 166,421 (52%). After requiring that other key variables (e.g. zipcode, house price index, etc.) are

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

non-missing, we are left with a final sample of 162,011 employees, working at 23,075 firms.

Neither the USPTO data nor the CoreLogic data give us detailed demographic characteristics for the employees in our sample. Therefore, we augment our data with information from LinkedIn. Among other things, LinkedIn provide information on educational background, work history, and job titles, even in non-patenting years. In order to match an employee in our sample with the employee's LinkedIn profile, we first find a set of potential profile URLs by using Google to search LinkedIn for profiles containing the employee name's in conjuction with various permutations and acronymizations of each firm the employee's patents have been assigned to. We then visit those LinkedIn profile URLs and determine based on further information (e.g. the timing of the position held relative to the timing of the patent application) whether the profile appears to be a match.[9]We are able to find a LinkedIn profile for 72,681 (45%) of the employees in our sample.

2.2 Key Variables

We use patent-based measures of an individual's innovative output that have been widely adopted over the past two decades (Jaffe and Trajtenberg, 2002; Lanjouw et al., 1998).[10] Our primary measure of the quantity of an individual's innovative output is the number of granted patents the individual applied for in a given year. It should be noted that employees likely have many productive activities they can engage in that do not have the potential to result in a patent. Engaging in these other activities may also be safer from the point of view of an employee in the sense that they carry a lower probability of failure. Thus, patenting output is not necessarily a good proxy for overall output, and an employee trying to increase job security may in fact produce fewer patents.

Our primary measure of the quality of an inventor's innovative output is 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. Specif-

[9]We only use data from public profiles, which we view as a non-logged-in user.
[10]Recent examples include Lerner et al. (2011); Aghion et al. (2013); Seru (2014).

ically, 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. We also 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.

We also characterize the nature of an employee's innovative output by computing patent "Originality" and "Generality" scores. 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. "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.[11] 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.

We attempt to measure the extent to which innovative output represents exploration versus

[11]When there are more citations, there is a mechanical tendency to cover more patent classes. To correct for this tendency we apply a bias adjustment suggested by Hall et al. (2001).

exploitation from the perspective of the firm. Exploratory innovation requires new knowledge, whereas exploitative innovation builds upon a firm's existing knowledge. In a sense, innovations that are more exploratory are likely to be more cited, influence subsequent innovations in a broader variety of fields, and rely on a larger variety of fields, as captured by patent citations, generality and originality measures.

To operationalize this concept more directly, we follow Brav et al. (2016), and 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. We also follow Chen Lin et al. (2016) and define a simple "New class" indicator variable equal to one if a patent is in a technology class the inventor's firm has never patented in before.[12]

In general, projects that result in patents that are highly cited, original/general, or exploratory are likely riskier for employees to pursue ex-ante. Therefore one could think of all of the measures above as measures of risk-taking. However, such projects are also likely more difficult. Thus, one could also consider the measures above as measures of complexity. It is difficult to separate these two dimensions of a project.

2.3 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.

[12] A large number of papers in the management literature define exploratory innovation in a similar fashion. In particular, risky, exploratory innovation is research which moves outside of a firm's knowledge base. Key papers in this literature include Jansen et al. (2006); Phelps (2010); Alexiev et al. (2010); Karamanos (2012).

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.

3 Empirical Strategy

Our primary interest is in how changes in house prices associated with the 2008 financial crisis affect the innovative output of employees. Because the 2008 crisis is a one time event that affects all individuals in our sample simultaneously, we rely on cross-sectional variation in which we compare innovative output across employees 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 individuals, and z indexes zip codes. The pre-period is defined as 2005–2007 and the post period is defined as 2008–2012. The variable $y_{i,post}$ represents the various patent-based measures of innovative output discussed in Section 2.2, including the total number of patents produced by individual i, the number of citations per patent, 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 individual i owned a house.

Equation 1 poses several potential concerns, as the location of an employee'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 individuals that worked at the same firm but lived in areas with differential house price declines during the crisis. Such individuals 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.[13] Assuming that the firms in our sample have only one office in the area surrounding a given city, these fixed effects will be equivalent to establishment fixed effects. Note that with firm by CBSA fixed effects we are identifying off of employees who worked at the same firm and owned a house in the same general area, but who experienced differential price declines in their respective zip codes.

This approach provides several advantages. First, the employees we compare are likely to be

[13]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 individuals 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 individuals, our CBSA fixed effects are effectively county fixed effects.

similar, as they operate in the same labor market, and are facing similar work opportunities outside of their firm. These employees 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 establishment 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 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 experienced by employees in the same firm and CBSA. We estimate that roughly 50% of the zip-code level price variation during the crisis occurred within CBSA. Figure 1 provides evidence that such variation is indeed present in the data. Panel A shows the distribution of housing price dispersion across different metropolitan areas. Darker areas represent CBSAs with higher price dispersion. Moreover, Panel B shows that the inventors in our sample also tend to live in such metropolitan areas with high housing price variance.

Even under this specification, however, one may worry that firms may have multiple establishments 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 output of two employees 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 individuals selecting into neighborhoods which were hardest hit by the crisis, were also those who decreased (or increased) their innovative output 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 employee characteristics as well as zip-code-level neighborhood 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 zip-code income level fixed effects. Section 4.3 provides greater detail on these specifications and discusses a variety of other such robustness tests. Our results remain unchanged with the inclusion of these controls.

Finally, to provide further evidence to 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 may be be smaller for some subgroups relative to others. For example, house price shocks may be less important for employees who face a thick outside labor market based on their field of expertise. These employees may be less concerned about losing their job when hit with a negative house price shock because finding a new job would be easier. Similarly, house price shocks may be less important for those who bought their house before the boom. These employees might be less concerned about losing their job when hit with a negative house price shock because they would have accumulated more home equity. Motivated by these observations, we estimate variants of Equation 2:

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

where $Characteristic$ is an employee level characteristic such as an indicator for whether the employee specialized in a popular technology, or an indicator for whether the employee bought before the housing boom. This specification allows us to test for heterogeneity in the effect of house price shocks. 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 employees 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 employees who choose to live in different zip codes because two employees who live in the same zip code should respond differently to the same house price shock.

4 Results

4.1 Main Findings

We begin in Table 2 by estimating variants of Equation 2. Standard errors are double clustered by firm and zipcode. In columns 1–2 we first examine the effect of changes in local house prices on the number of patents an employee 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 employees who work at the same firm and own a house in the same area, but live in different zip codes. Comparing such employees further helps to minimize selection concerns, as these individuals 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 employee lives is strongly associated with lower patenting output. In column 2 we also include as an additional control the change in house prices that an employee'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 employees 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 4.3, we also find that our estimates remain unchanged after controlling for additional employee 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 employee'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. 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.

In Table 4 we begin to investigate the nature of innovations produced by employees living in areas differentially affected by the crisis, focusing first on generality and originality. As discussed in Section 2.2, 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. We find that employees 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.

Finally, in Table 3 we further investigate whether the patents of employees that experience larger house price declines during the crisis become less exploratory in the sense that they rely more heavily on the existing knowledge of their firm. As discussed in Section 2.2, 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 employees pursue less exploration when they experience a negative shock to their outside wealth, we find in columns 1–2 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 employee'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.

As illustrated in Panels (c) through (f) of Figure 2, the effect of housing prices on originality, generality, and exploration 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.

Overall, the results so far suggest that following a housing wealth shock, employees become more conservative and less likely to pursue high impact, exploratory, and complex projects. In fact, employees that are most severely affected by the housing shock adjust their innovative projects most strongly. The results thus far are inconsistent with the hypothesis that household wealth shocks does not affect employee innovation because employees cannot adjust their innovative projects. Moreover, these results are also inconsistent with the hypothesis that the hardest hit employees "swing for the fences" because of the decreased benefit from maintaining mortgage payments.

4.2 Individuals Remaining at the Same Firm

Do these effects arise from changes in the incentives of employees 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 individuals working within a firm, we repeat our baseline analysis among individuals who remain at the same firm. We identify employees 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 employees remained at the same firm during the crisis.

If changes in innovative output arise only from employees 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, in contrast to this view, we find that our main results hold for the employees 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 employees choose less exploratory projects which are also less general and original in nature. Thus, the changes in project selection occur for employees 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 employee in the post-crisis period while in the same firm, this analysis also implies that the results are not driven by employees becoming non-research-active due to retirement or death.

4.3 Selection Concerns

In section 3 we discuss how concerns about selection issues motivated the design of the empirical strategy in the paper. Specifically, unobserved differences between firms, and across geographical areas lead us to include firm by CBSA fixed effects in the baseline specifications, and thus effectively comparing employees working at the same firm and reside in the same metropolitan area. In the next section we explore more nuanced selection concerns within the firm, by including more flexible and demanding fixed effects controls.

4.3.1 Technology

One potential concern is that we might be comparing employees 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 include firm by CBSA by employee technology class fixed effects. The results are in Row 2 of Table 6, Panel A. We define an employee's technology class to be the modal 3-digit class of the employee's patents in the pre-crisis period. This specification is very conservative in that it only identifies off of variation from employees 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, which are presented in Row 1 for convenience.

4.3.2 Neighborhood Characteristics

Next, we explore the impact of employee sorting into different types of neighborhoods within CBSA (while working at the same firm). We begin by focusing on the average income level of the zip-code in which an employee lives. This specification attempts to address the concern that employees with higher wages may sort into richer neighborhoods, and therefore may experience different housing price shocks while facing differential risks of job termination during the crisis. In Row 3 of Table 6, Panel A we sort employees into quartiles within each CBSA, based on the 2000 mean income level of the zip-code in which they live. We then run our regressions with CBSA by firm by neighborhood income quartiles fixed effects. These regressions compare two employees who work at the same firm, live in the same CBSA, and live in zip-codes of similar mean income level in the CBSA. The results are consistent with our baseline specification and remain unchanged.

In Row 4 of Table 6, Panel A sort employees into quartiles within a CBSA 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 zip-code family size fixed effects. This specification is yet another check for the concern that employees with children, who likely sort into more family-oriented neighborhoods, were more concerned about job termination during the crisis while at the same time may experience a different housing price shocks. To further address this point, in Row 5 we sort employees into quartiles (within CBSA) based on the 2000 census measure of how urban their resident zip-code and then include CBSA by firm by zip-code urban measure quartiles fixed effects. It seems likely that single employees put less of a premium on space and are thus likely to live in the city center than employees with families. In both specifications, our estimates are very similar to the baseline results.

An additional attempt to explore slightly more directly potential selection issues related to employee wages and family is to include fixed effects based on the square-footage of the house the employees own in 2007. It seems likely that employees 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 employees into quartiles based on the square-footage of the house owned in 2007 (within CBSA), and run the regressions with CBSA by firm by square-footage quartiles fixed effects. This specification compares two employees 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.

4.3.3 Employee Characteristics

In this section we explore various employee characteristics that may correlate with employee sorting into different zip-code areas within CBSA. One such selection story is that less experienced employees 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 recession, which thus impacted their willingness to take risks. Alternatively, firms may have cut back on innovation during the recession and re-assigned the least experienced employees to projects less focused on important, cutting-edge innovation. To address this possibility, for each employee we calculate experience as the number of years, as of 2007, since the employee's first patent and sort employees into experience quartiles. We then re-run our regressions with firm by CBSA by experience quartile fixed effects. This specification compares two employees of similar experience level, working at the same firm, and living in the same CBSA. We report the results in Row 7 of Table 6, Panel A. Our results are very similar to the baseline specification reported in row 1.

Similar to experience, it may be that younger employees, less educated employees, or employees 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 employees tend to systematically live in different zip codes than older employees. For instance, younger employees may be more likely to live in the city center, while older workers tend to live more in the suburbs. Similarly, employees 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 employee 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 similar.

The LinkedIn data provide information on employee age, education, employment history, and position within the firm. We calculate age as the number of years, as of 2007, since the employee's first degree, plus 22. We then sort employees 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 employee 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 quartiles 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.

4.4 Robustness Tests

In this section, we perform a battery of robustness tests to handle additional potential concerns.

Excluding 2008-2009 Patent Grants

One potential concern is that the patenting process takes time and our results may therefore reflect research initiated prior to the start of the housing crisis. To handle this potential measurement problem, we re-run our main specifcation excluding all patent grants betwen the years of 2008-2009. The results are reported in Table A.1. As the table shows, all of our results continue to come through.

Shorter Time Horizons

We also verify that the results are driven by the declines in housing prices during the crisis rather than by the recovery process that took place only a few years later. For this reason we focus on housing price fluctuations during the first year of the crisis, and the first 3 years of the crisis. The results are reported in the Appendix in tables A.3 and A.2. In fact, we illustrate that the results hold also when using a one year housing price changes, and focusing on the subsequent patenting activity of inventors, when excluding years 2008 and 2009 from the sample.

Conditioning on Patenting Post-Crisis

One possibility is that our results are primarily driven by individuals who have no patents in the post-crisis period, i.e. inventors who simply stop patenting. To explore this, we re-run our main specification for only those inventors who patented both before and after the crisis. We report the results in Table A.5. We find that the estimated effects on number of patents and number of citations continue to be highly signficicant, although the magnitudes are somewhat smaller. Thus, our results on patent and citation counts are certainly not driven solely by inventors who stop patenting post-crisis. We find that all of our other results remain essentially unchaged when we restrict to inventors who patent both pre and post crisis.

Firm Size

Yet another concern is that our results are driven by inventors working at only a few large firms. In Table A.6,we therefore report our results for subsamples based on firm size. In particular, we run our main specification for only inventors working at firms with less than 1000 inventors, at firms with less than 100 inventors, at firms with less than 50 inventors, at firms with less than 30 inventors, and at firms with less than 10 inventors. For medium sized firms with less than 1000 inventors or less than 100 inventors, all of our estimated effects continue to come through and are statistically significant. We we restrict to only the smallest firms, standard errors are higher as is to be expected. For number of patents and generality, we continue to estimate positive effects, although the magnitudes are smaller and the effects are not statistically significant. For all other dependent variables, however, even restricting to only the smallest firms in our sample, we continue to estimate highly significant effects of similar magnitude.

Alternative Price Measures

Our zipcode level house price indexes are provided by Bogin et al. (2016). A potential concern is that our results are sensitive to the details of the construction of this dataset. To deal with this, we re-run our main specifications with zipcode level price indexes provided by Zillow. The results are reported in Table A.7. All of our results remain unchanged.

5 Heterogeneity

In this section, we explore the heterogeneous effects of labor market outside options and and the impact of housing equity. The benefits of this exploration are as follows. First, as discussed in Section 3, studying heterogeneity allows us to include zipcode level fixed effects, which provides yet another way to control for employee sorting within metropolitan area and the resulting selection concerns. Second, studying heterogeneity allows us to document various ameliorating factors for the impact of housing price decreases on employee output and innovation in particular, which may be of interest to both market participants and policymakers. Finally, as we discuss in Section 6, the heterogeneity analysis sheds useful evidence on the potential underlying channels, particularly given that both housing equity and employment opportunites are highlighted mortgage default literature as two prominent factors affecting household default risk (e.g., Foote et al., 2008, 2010)).

5.1 The Impact of Labor Market Outside Options

We begin by investigating how our results depend on the labor market outside options of inventors. To do this, 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. 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-crisis 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 3, 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 having different outside labor market opportunities.[14] 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 those employees, within the same firm, that are facing a greater set of outside labor market opportunities.

[14]Note that this is a more demanding specification than the one used in previous results where we incorporate CBSA X Firm fixed effects. We can control for zipcode fixed effects in this specification because we estimate the interaction of housing prices changes with the labor market outside options variable. We cannot control for zipcode fixed effects to estimate the direct effect of housing prices changes. The results in this section hold also when we simply control for CBSA X Firm fixed effects. However, due to power limitations, we are not able to include firm by zipcode fixed effects. We are able to add both firm fixed effects and zipcode fixed effects.

5.2 The Impact of Housing Equity

Next, we examine whether the strength of our baseline results varies with the amount of housing equity the inventor entered the crisis with. We proxy for this by exploiting the timing in which employees bought their house. Employees who bought their house during the boom (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.

We estimate Equation 3 with zip code and firm fixed effects, this time interacting house price shocks with an indicator equal to one if the employee bought their house prior to 2005.[15] 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 in fact *smaller* for employees who bought their house earlier, and thus were likely to accumulate more equity in the house. We discuss the implications of both these heterogeneity results in the following section.

6 Potential Channels

The primary contribution of this paper is to establish that household wealth shocks do affect employee output, thus linking household balance sheets to the innovative output at the firms. Overall, the evidence suggests that following a housing wealth shock, employees are less likely to successfully pursue innovative projects, particularly ones that are high impact, exploratory, or complex in nature. In this section, we discuss potential channels through which these effects may operate. In particular, we consider whether changes employee behavior are driven by wealth losses, or concerns

[15]Similarly to the analysis of the labor market outside options, it is worth noting that this specification is more demanding than the one used in the main results where we incorporate CBSA X Firm fixed effects. We can control for zipcode fixed effects in this specification because we estimate the interaction of housing prices changes with home ownership duration. We cannot control for zipcode fixed effects to estimate the direct effect of housing prices changes. The results in this section hold also when we simply control for CBSA X Firm fixed effects. However, due to power limitations, we are not able to include firm by zipcode fixed effects. We are able to add both firm fixed effects and zipcode fixed effects.

about potentially costly mortgage default.

6.1 Wealth Effects

One possibility is that employee preferences exhibit decreasing absolute risk aversion. In this case, following a negative wealth shock, employees would become more risk-averse, leading them to pursue safer, less innovative projects. To the extent that risk-averse employees can in fact shift their effort toward safe (yet productive) projects that lack the potential to result in a patent, such wealth effects could lead not only to a change in the nature of an employees' innovative output but also a decline in the quantity of that output. To examine whether wealth effects drive our baseline results, we examine the impact of housing price increases on innovation during the housing boom which preceded the housing crisis. Under the wealth effects channel, we would expect our results to be symmetric during the housing boom. That is, employees who experienced an increase in housing wealth should have become more risk tolerant and thus more willing to pursue innovative projects.

To test this, we again estimate Equation 2, our baseline specification that includes CBSA by firm fixed effects. This time, we focus on a sample of employee homeowners that have at least a single patent in the years 1999-2001 and explore how subsequent house price increases, during the boom period of 2002-2007, affect employee innovation and risk taking. Table 9 shows that there is no effect of house price changes for any of our outcomes during the boom period, inconsistent with the wealth effect channel.

Moreover, as we discuss in Section 5.2, we find that employees who bought their house earlier, before the boom, and who are therefore more likely to have had more equity at the onset of the crisis, were less sensitive to the shock, and experienced a smaller decline in innovative output. This is again inconsistent with the wealth effects channel since those who had more equity, if anything, experienced a larger wealth loss when house prices decline, than those who hit the zero equity bound. Therefore, based on the wealth effect channel, they should experience a larger decline in innovative output due to a greater increase in risk aversion, in contrast to our finding. Overall, the empirical findings are not supportive of the view that wealth effects per se can explain the decline in employees' innovative activity.

6.2 Effects of Financial Distress

An alternative possibility is that employees produce less innovative output following a decline in housing prices as a result of financial distress concerns. This could be true even if employees were risk neutral. For instance, there is substantial empirical evidence that motgage default is costly for households. A family experiencing foreclosure likely has to incur significant moving costs due to the forced relocation. Children may be uprooted from their current school and could suffer educationally (Been et al., 2011). Credit scores are negatively and persistently impacted by a foreclosure, which can adversely affect future employment outcomes (Brevoort and Cooper, 2013). Finally, households may wish to avoid default to the extent that they view it as a significant personal failing or immoral, or to the extent that that there is a social stigma attached to defaulting on one's debt obligations. Using survey data, Guiso et al. (2009) find that, after relocation costs, the most important determinants of strategic default are moral and social considerations.

The literature on mortgage default emphasizes the "double-trigger" model as an important explanation for changes in default risk, by attributing default to negative home equity, particularly when combined with a negative life event such as unemployment (e.g., Foote et al., 2008, 2010). Specifically, a borrower whose home equity becomes negative is likely to default if he or she also experiences a sufficiently severe income shock, typically in the form of unemployment. Once the borrower runs out of liquid financial resources, mortgage payments cannot be paid and default is inevitable, as not even a quick sale can pay off the outstanding balance. Hence, this literature highlights the combination of negative equity and unemployment risks as potentially important factors that can increase mortgage default risk (Bhutta et al., 2017; Gerardi et al., 2013; Gyourko and Tracy, 2014; Niu and Ding, 2015).

In light of the potential costs of default, employees who have experienced a major house price decline may be distracted by stress and anxiety, for example, since they are more vulnerable to being forced into default (Currie and Tekin, 2015; Deaton, 2012). This distraction may reduce their ability to effectively produce innovative output. In addition, such employees may also actively try to increase their job security to mitigate the risk of a second default trigger, that is, unemployment. They may do this by pursuing safer projects. For example, employees may pursue projects that exploit existing knowledge and thus have a lower probability of failure, rather than pursue projects that explore new and uncertain technologies (Manso, 2011). In both cases, it is the prospect of costly default that leads to less innovation. We formally model this costly default channel in the appendix using a variant of the Holmström (1999) work on incentive provision through career concerns.

Of course, the inventors in our sample are likely not poor individuals. Most of the inventors in our sample are college educated and, in 2007, were working in technical fields offering a decent wage. Therefore, to the extent that the housing crisis was concentrated among the poorest households, the validity of the story outlined thus far would be weakened. However, empirical work (e.g. Mian and Sufi (2016), Foote el at., 2016; Adelino et al. (2016)) has shown that the the expansion of credit in the run-up to the crisis was not solely confined to the poorest houesholds. The mortgage debt of higher income households also significantly expanded between the years 2001-2007. As a result of this expansion in mortgage debt, higher income households also became underwater during the crisis and were subject to the associated deliquency risk. Indeed, while empirical work has shown that the level of foreclosures was highest among among low income, subprime borrowers, the rate of foreclousres increased subtantially for both low income and high income houseolds during the crisis.[16]

Moreoever, even if a household does not default, being underwater itself has its own attendant and significant financial distress costs, especially in the event of lost income. First, underwater homeowners cannot take out a home equity loan to smooth consumption. Even more importantly, underwater homeowners may likely be unable to sell, since the proceeds would be insufficient to cover the mortgage balance, a phenomenon generally known as lock-in. This means that in the event of job loss, it could be difficult to re-locate to take on another job. Also, in the event that

[16]Foote el at., 2016 and Adelino et al. (2016) argue that, in percentage terms, the increase in the rate foreclosures was actually highest among high income households. Empirical work on these issues continues.

another source of income could not be found, since the household would not have the option of selling, the household may likely have to cut back significantly on consumption or dip into savings to avoid a costly default. In the context of our setting, all of these concerns would work to increase an inventor's desire for job security and may lead her to pursue safer projects. Finally, as a result of all the related costs, being underwater itself likely carries its own mental stress issues, which could impair cognitive ability and negatively impact job performance.

Our empirical findings are consistent with the financial distress channel. As discussed in Section 5.2, we find that employees who are likely to have had more equity in their house at the onset of the crisis, who were therefore less likely to have had the negative equity trigger, experienced a smaller decline in innovative output. Moreover, as discussed in Section 5.1, we find that employees with more outside labor market opportunities, who therefore were less likely to have had the unemployment– trigger, also experienced a smaller decline in innovative output. Together, these results are consistent with the double-trigger financial distress model, which emphasizes that the impacts of a housing crisis are particularly servere for individuals who experience both negative equity and job loss(e.g., Foote et al., 2008, 2010). Consistently, we find that employees with higher equity in their house, and greater labor market opportunities seem to experience a lower sensitivity to housing wealth shocks, arguably due to a lower default risk. These results may be of particular interest to policymarkers tasked with developing appropriate housing related macroprudential policy.

6.3

7 Conclusion

In this paper, we investigate whether household level shocks impact employee output in firms through the lens of technological innovation. The household level shocks that we focus on are changes in housing wealth experienced by employees during the financial crisis. Throughout the paper, we compare employees that worked at the same firm and lived in the same metropolitan area, but experienced different housing wealth declines during the crisis. Using this empirical strategy, we find that employees who experience a negative shock to housing wealth are less likely to successfully pursue innovative projects, particularly ones that are high impact, exploratory, or complex in nature.

These findings are most consistent with the hypothesis that negative housing wealth shocks lead to decreased innovative output due to heightened concerns among employees about the possibility of mortgage default. Consistent with this hypothesis we find that the effects are less pronounced among employees that are at a lower risk of facing mortgage default. That is, we find that housing wealth shock particularly affect the productivity of employees with fewer outside labor market opportunities, and of employees who had little equity in their house before the crisis. These results may also be of interest to policymakers concerned with macroprudential policy related to the housing market, such as the appropriate level of Loan-to-Value requirements.

Finally, our results also shed light on the origins of innovation within the firm. 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 places a significant impact on the types of innovative projects a firm pursues, highlighting the role of lower ranked employees in shaping the innovation at the firm.

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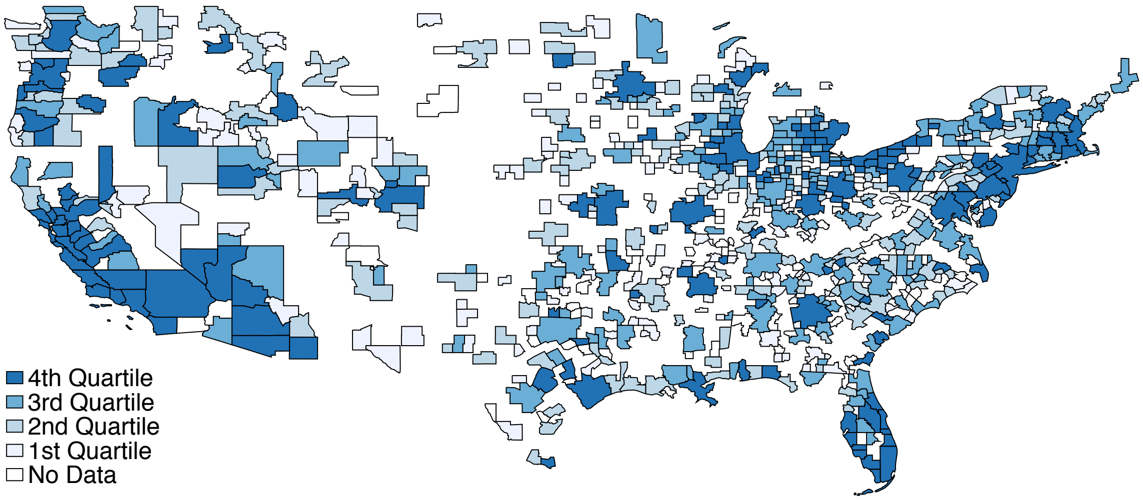
Figure 1

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**

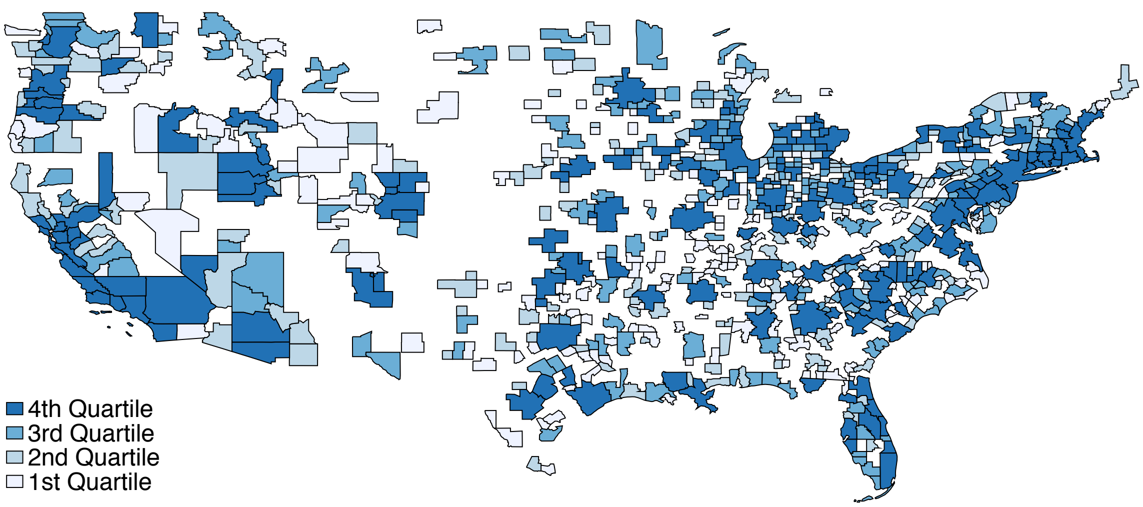
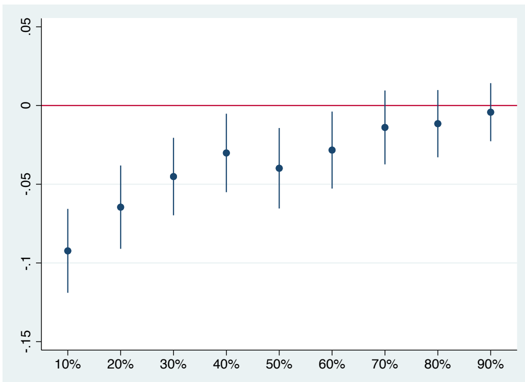


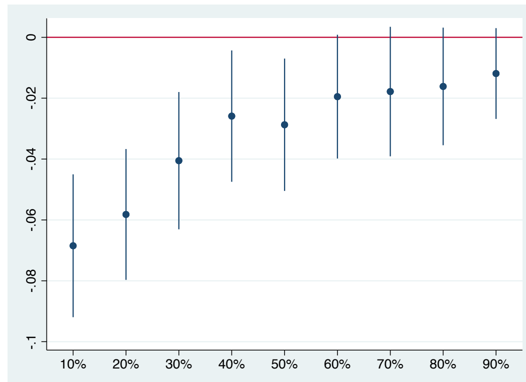
Figure 2
Treatment Intensity

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.

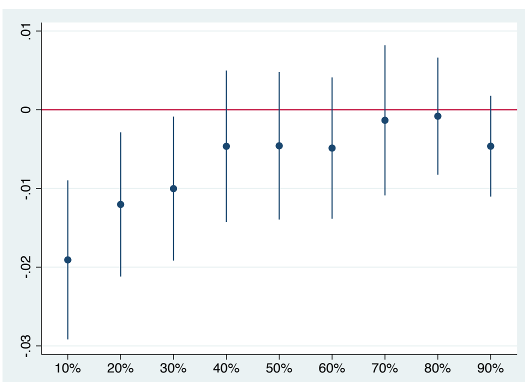
(a) **Number of Patents**



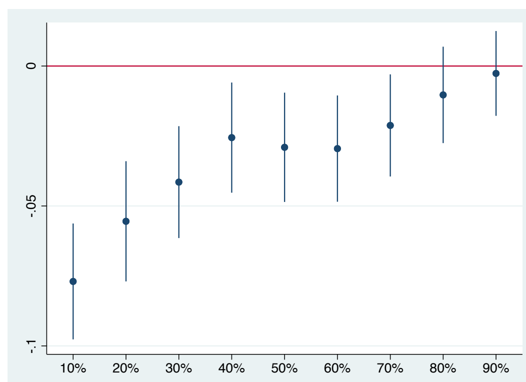
(b) **Citations per Patent**



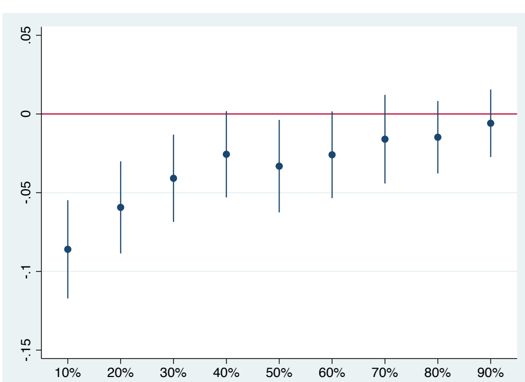
(c) **New Technology**



(d) **Exploratory Patents**



(e) **Originality**



(f) **Generality**

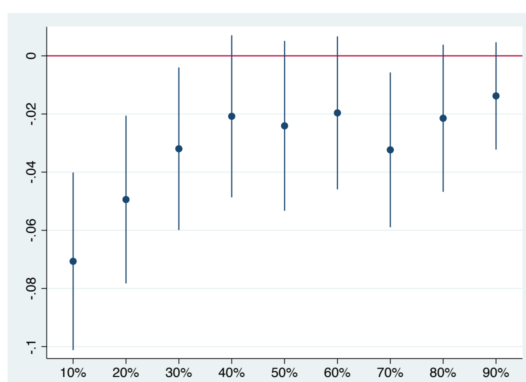


Table 1
Summary Statistics

Panel A of this table shows summary statistics for patent measures used in the analysis. The patent variables are measured over the years 2008–2012. *Number of Patents* is defined as the number of eventually granted patents applied for by an inventor during the period. *Normalized Citations Per Patent* is the total number of normalized citations received by an inventor's patents, divided by *Number of Patents*. A patent's normalized citations are its total citations received divided by the mean number of citations received by patents granted in the same year and technology class. *Number of Top Cited Patents* counts the number of an inventor's patents that were in the top 10% of all patents granted in the same year and technology class in terms of citations. *New Class Indicator* is an indicator variable equaly to one if any of the inventor's patents were in a technology class the inventor's firm has never patented in before. *Number of Exploratory Patents* counts the number of an inventor's patents that are exploratory in the sense that less than 20% of the patents they cite are 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. *Normalized Generality Per Patent* is defined as the average normalized generality for an inventor's patents. Normalized generality scales generality by the mean value of generality for all patents granted in the same year and technology class. Generality is equal to one minus the Herfindahl-Hirschman Index (HHI) of forward citations across technology classes. *Normalized Originality Per Patent* is defined analgously to *Normalized Generality Per Patent* but with respect to backward citations rather than forward citations.

Panel A: Patent Measures (2008-2012)

Variables	Obs	Mean	Std Dev
Log(Number of Patents)	162,011	0.64	0.80
Log(Normalized Citations Per Patent)	162,011	0.27	0.50
Log(Number of Top Cited Patents)	162,011	0.17	0.44
New Technology Indicator	162,011	0.09	0.28
Log(Number of Exploratory Patents)	162,011	0.23	0.47
Log(Normalized Generality Per Patent)	162,011	0.15	0.33
Log(Normalized Originality Per Patent)	162,011	0.35	0.38

Table 1
(Continued)

Panel B shows summary statistics for characteristics of employees in our sample as of 2007. The *Degree* variables are dummy variables equal to one if the employee holds the stated degree (employees can have multiple degrees). The variable *Age* is defined as 2007 minus the year the employee first obtained a degree plus twenty-two. The variable *Work Experience* is equal to 2007 minus the start year of the employee's first work position. The variable *Tenure at Firm* is equal to 2007 minus the start year of the employee's 2007 work position. The variable *Senior Position* is an indicator equal to one if the inventor's position title includes managerial keywords (CEO, chair, chairman, chief, CTO, director, executive, head, management, manager, partner, president, principal, VP). Panel C shows summary statistics for house characteristics of employees in our sample as of 2007. The variable *Years Owned House* is the years the employee had owned the house as of 2007, *Square footage* is the size of the employee's house as of 2007, *Age of House* is the age of the house in years as of 2007, %Δ*House Price Pre* is the percent change in house prices in the zip code of the inventor's house from the end of 2004 to the end of 2007, %Δ*House Price Post* is the percent change in house prices in the zip code of the inventor's house from the end of 2007 to the end of 20012.

Panel B: Employee Characteristics (2007)

Variables	Obs	Mean	Std Dev
BA Degree	58,750	0.97	0.17
MA Degree	58,750	0.30	0.46
PhD Degree	58,750	0.28	0.45
MBA Degree	58,750	0.09	0.29
JD Degree	58,750	0.01	0.09
MD Degree	58,750	0.01	0.09
Age	49,077	41.14	8.93
Work Experience	61,180	15.60	8.37
Tenure at Firm	57,892	6.47	6.86
Senior Position	69,930	0.48	0.50

Panel C: Employee House Characteristics (2007)

Variables	Obs	Mean	Std Dev
Years Owned House	157,194	7.66	5.91
Square Footage	107,074	2952.73	1919.70
Age of House	144,747	29.77	26.85
%Δ House Price Pre (2004-2007)	162,011	0.22	0.15
%Δ House Price Post (2007-2012)	162,011	-0.16	0.13

Table 1
(Continued)

Panel D shows the distribution of employees across fields. Employees are categorized using their modal NBER technology subcategory for patents applied from from 2005–2007. Panel E shows the correlation among the patent measures from Panel A.

Panel D: Distribution of Employees Across Fields (2007)

NBER patent subcategory	Freq	Percent
Computer Hardware & Software	19,139	11.82
Communications	16,654	10.28
Drugs	13,123	8.10
Chemical (miscellaneous)	9,067	5.60
Electronic Business Methods and Software	8,194	5.06
Surgery and Medical Instruments	7,403	4.57
Semiconductor Devices	7,251	4.48
Information Storage	6,659	4.11
Power Systems	5,846	3.61
Measuring & Testing	5,467	3.38
Mechanical (miscellaneous)	4,714	2.91
Transportation	3,874	2.39
Electrical Devices	3,767	2.33
Computer Peripherals	3,452	2.13
Materials Processing and Handling	3,268	2.02
Motors, Engines and Parts	3,159	1.95
Electrical and Electronics (miscellaneous)	2,961	1.83
Resins	2,913	1.80
Nuclear, X-rays	2,540	1.57
Organic compounds	2,432	1.50

Panel E: Patent Measure Correlation Matrix (2008-2012)

	Cites	Top	New	Explore	Gen	Orig
Log(Normalized Citations Per Patent)	1					
Log(Number of Top Cited Patents)	0.737	1				
New Technology Indicator	0.231	0.255	1			
Log(Number of Exploratory Patents)	0.317	0.448	0.410	1		
Log(Normalized Generality Per Patent)	0.834	0.617	0.191	0.257	1	
Log(Normalized Originality Per Patent)	0.545	0.406	0.295	0.425	0.471	1

Table 2

Quantity and Quality of Innovation

This table estimates the effect of changes in zipcode level house prices on the quantity and quality of innovative output for patent inventors who 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 within firms who are research-active as of onset of the crisis in 2008 (i.e., were credited on at least one assigned patent in the pre-period). All variables are as defined in Table 1. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Number of Patents Post)		Log(Citations Per Patent Post)		Log(Top Cited Patents Post)	
	(1)	(2)	(3)	(4)	(5)	(6)
%Δ House Price Post	0.218***	0.219***	0.172***	0.172***	0.135***	0.135***
	(0.0317)	(0.0316)	(0.0240)	(0.0239)	(0.0190)	(0.0189)
%Δ House Price Pre		-0.0310		0.00866		0.00904
		(0.0523)		(0.0432)		(0.0343)
Pre-2008 Measure	0.789***	0.789***	0.212***	0.212***	0.416***	0.416***
	(0.0205)	(0.0205)	(0.00895)	(0.00896)	(0.0138)	(0.0138)
Firm × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.290	0.290	0.048	0.048	0.157	0.157
Observations	162,011	162,011	162,011	162,011	162,011	162,011

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 within firms who are research-active as of onset of the crisis in 2008 (i.e., were credited on at least one assigned patent in the pre-period). All variables are as defined in Table 1. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	New Class Indicator Post		Log(Exploratory Patents Post)	
	(1)	(2)	(3)	(4)
%Δ House Price Post	0.0486***	0.0489***	0.188***	0.188***
	(0.0118)	(0.0118)	(0.0237)	(0.0236)
%Δ House Price Pre		-0.0265		0.0309
		(0.0186)		(0.0399)
Pre-2008 Measure	0.0756***	0.0756***	0.277***	0.277***
	(0.00431)	(0.00431)	(0.0105)	(0.0105)
Firm × CBSA FE	Yes	Yes	Yes	Yes
R^2	0.008	0.008	0.077	0.077
Observations	162,011	162,011	162,011	162,011

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 within firms who are research-active as of onset of the crisis in 2008 (i.e., were credited on at least one assigned patent in the pre-period). All variables are as defined in Table 1. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, 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	0.0922***	0.0921***	0.156***	0.156***
	(0.0163)	(0.0163)	(0.0195)	(0.0194)
%Δ House Price Pre		0.00317		-0.00821
		(0.0277)		(0.0328)
Pre-2008 Measure	0.123***	0.123***	0.192***	0.192***
	(0.00479)	(0.00479)	(0.00754)	(0.00754)
Firm × CBSA FE	Yes	Yes	Yes	Yes
R^2	0.023	0.023	0.010	0.010
Observations	162,011	162,011	162,011	162,011

Table 5
Inventors Remaining at Same Firm

This table repeats the analysis of Tables 2–4, limiting the sample to inventors who are observed patenting at their pre-crisis firm or who list themselves as still employed at their pre-crisis firm on LinkedIn after our estimation period ends in 2012. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, 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	0.296***	0.246***	0.223***	0.0637***	0.240***	0.131***	0.181***
	(0.0562)	(0.0364)	(0.0338)	(0.0177)	(0.0401)	(0.0268)	(0.0269)
Pre-2008 Measure	0.757***	0.263***	0.465***	0.0986***	0.310***	0.162***	0.257***
	(0.0225)	(0.0120)	(0.0149)	(0.00664)	(0.0128)	(0.00727)	(0.0116)
Firm × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.308	0.066	0.178	0.012	0.088	0.033	0.020
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 but allowing the firm by CBSA fixed effects to interact with various other 2007 characteristics. For brevity, only the main coefficient on *%Δ House Price Post* is shown, but other controls remain similar. *Tech Class* is the modal 3-digit technology class of the inventor's patents in the pre-period. The variables *Neighborhood Income Q.*, *Square Footage Q.*, *Urban Neighborhood Q.*, and *Family Neighborhood Q* are quartiles of the respective variables. *Patent Experience Q.* are quartiles based on the number of years since the inventor's first patent (as of 2007). *Age Q.* are quartiles based on the number of years since the inventor's first degree (as of 2007), plus twenty-two. *Education* represent the inventor's highest degree as defined in Panel A of Table 1. *Senior Position* is an indicator equal to one if the inventor's position title includes managerial keywords (CEO, chair, chairman, chief, CTO, director, executive, head, management, manager, partner, president, principal, VP). Panel A specifications use the full sample, while Panel B specifications use only inventors with available information on LinkedIn. Standard errors are clustered by firm and inventor residential zipcode. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Fixed Effects Specification	(1) Num	(2) Cites	(3) Top	(4) New	(5) Explore	(6) Gen	(7) Orig
Panel A: Full Sample							
(1) Firm × CBSA FE	0.218***	0.172***	0.135***	0.0486***	0.188***	0.0922***	0.156***
	(0.0317)	(0.0240)	(0.0190)	(0.0118)	(0.0237)	(0.0163)	(0.0195)
(2) Firm × CBSA × Tech Class FE	0.172***	0.143***	0.134***	0.0326**	0.169***	0.0968***	0.119***
	(0.0368)	(0.0262)	(0.0233)	(0.0139)	(0.0281)	(0.0176)	(0.0209)
(3) Firm × CBSA × Neighborhood Income Q. FE	0.201***	0.143***	0.107***	0.0464***	0.183***	0.0819***	0.147***
	(0.0398)	(0.0332)	(0.0265)	(0.0152)	(0.0312)	(0.0220)	(0.0231)
(4) Firm × CBSA × Family Neighborhood Q. FE	0.198***	0.166***	0.127***	0.0561***	0.184***	0.0870***	0.143***
	(0.0401)	(0.0309)	(0.0239)	(0.0145)	(0.0320)	(0.0226)	(0.0239)
(5) Firm × CBSA × Urban Neighborhood Q. FE	0.232***	0.186***	0.142***	0.0600***	0.199***	0.0936***	0.170***
	(0.0334)	(0.0285)	(0.0212)	(0.0138)	(0.0264)	(0.0201)	(0.0224)
(6) Firm × CBSA × Square Footage Q. FE	0.193***	0.160***	0.124***	0.0382***	0.162***	0.0876***	0.138***
	(0.0334)	(0.0273)	(0.0212)	(0.0128)	(0.0269)	(0.0185)	(0.0201)
(7) Firm × CBSA × Experience Q. FE	0.191***	0.142***	0.111***	0.0480***	0.151***	0.0741***	0.115***
	(0.0325)	(0.0246)	(0.0201)	(0.0126)	(0.0256)	(0.0172)	(0.0176)
Panel B: LinkedIn Sample							
(1) Firm × CBSA FE	0.218***	0.172***	0.135***	0.0486***	0.188***	0.0922***	0.156***
	(0.0317)	(0.0240)	(0.0190)	(0.0118)	(0.0237)	(0.0163)	(0.0195)
(2) Firm × CBSA × Age Q. FE	0.309***	0.241***	0.181***	0.0332	0.295***	0.146***	0.202***
	(0.0721)	(0.0563)	(0.0532)	(0.0255)	(0.0505)	(0.0361)	(0.0441)
(3) Firm × CBSA × Education FE	0.224***	0.186***	0.128***	0.00618	0.180***	0.118***	0.174***
	(0.0549)	(0.0415)	(0.0375)	(0.0186)	(0.0424)	(0.0290)	(0.0287)
(4) Firm × CBSA × Senior Position FE	0.284***	0.231***	0.176***	0.0335**	0.237***	0.131***	0.199***
	(0.0530)	(0.0412)	(0.0367)	(0.0169)	(0.0412)	(0.0285)	(0.0283)

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 three years before the crisis (2005–2007). 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 inventor residential zipcode. *,**, 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 ×	-0.118**	-0.0417**	-0.0638***	0.0217	-0.0434	-0.0560***	-0.0567**
Popular Technology	(0.0530)	(0.0210)	(0.0244)	(0.0144)	(0.0290)	(0.0203)	(0.0282)
Pre-2008 Measure	0.789***	0.134***	0.413***	0.0760***	0.271***	0.126***	0.191***
	(0.0183)	(0.00617)	(0.0120)	(0.00378)	(0.00935)	(0.00447)	(0.00721)
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.470	0.292	0.369	0.328	0.276	0.279	0.263
Observations	162,011	162,011	162,011	162,011	162,011	162,011	162,011

Table 8
House Ownership Duration

This table repeats the analysis of Tables 2–4, now allowing *%Δ House Price Post* to interact a *Purchased before 2004* indicator equal to one if the inventor's house was purchased prior to 2004. Standard errors are clustered by firm and inventor residential zipcode. *,**, 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 ×	-0.0985***	-0.0572***	-0.0361*	0.00348	-0.00889	-0.0341**	-0.0407**
Purchase before 2004	(0.0370)	(0.0173)	(0.0191)	(0.0129)	(0.0265)	(0.0163)	(0.0200)
Pre-2008 Measure	0.790***	0.134***	0.413***	0.0763***	0.270***	0.126***	0.193***
	(0.0181)	(0.00614)	(0.0120)	(0.00377)	(0.00926)	(0.00445)	(0.00725)
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.473	0.293	0.370	0.328	0.277	0.279	0.264
Observations	162,011	162,011	162,011	162,011	162,011	162,011	162,011

Table 9
Housing Prices Effects in 2002

This table repeats the analysis of Tables 2–4, but estimates the effect of changes in zi 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 within firms who are research-active as of onset of the crisis in 2008 (i.e., were credited on at least one assigned patent in the pre-period). All variables are as defined in Table 1. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, 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	-0.0696	-0.0114	-0.0219	-0.0202	-0.0515	-0.0245	-0.0338
	(0.0476)	(0.0255)	(0.0226)	(0.0140)	(0.0319)	(0.0221)	(0.0232)
Pre-2002 Measure	0.539***	0.154***	0.253***	0.0442***	0.178***	0.118***	0.163***
	(0.0247)	(0.00679)	(0.0113)	(0.00387)	(0.0102)	(0.00575)	(0.00809)
Firm $\times$ CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.105	0.028	0.061	0.003	0.029	0.009	0.005
Observations	161,887	161,887	161,887	161,887	161,887	161,887	161,887

Appendix

A Tables

Table A.1
Excluding 2008-2009 Patents

This table repeats the analysis of Tables 2–4, now excluding patents applied for in 2008-2009 from the outcome variables. Standard errors are clustered by firm and inventor residential zip code. *,**, 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	0.149***	0.136***	0.0915***	0.0317***	0.109***	0.0694***	0.128***
	(0.0249)	(0.0215)	(0.0141)	(0.00874)	(0.0167)	(0.0135)	(0.0183)
Pre-2008 Measure	0.544***	0.161***	0.265***	0.0380***	0.145***	0.0784***	0.143***
	(0.0137)	(0.00769)	(0.0104)	(0.00305)	(0.00612)	(0.00452)	(0.00692)
Firm × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.223	0.033	0.112	0.004	0.044	0.013	0.006
Observations	162,011	162,011	162,011	162,011	162,011	162,011	162,011

Table A.2
Three-Year House Price Changes

This table repeats the analysis of Tables 2–4, redefining %Δ *House Price* to represent the zipcode level change in house prices from 2007 to 2010, rather than 2007 to 2012. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, 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	0.264***	0.192***	0.154***	0.0489***	0.203***	0.100***	0.177***
	(0.0378)	(0.0282)	(0.0238)	(0.0147)	(0.0292)	(0.0194)	(0.0237)
Pre-2008 Measure	0.789***	0.212***	0.416***	0.0756***	0.277***	0.123***	0.192***
	(0.0204)	(0.00894)	(0.0138)	(0.00431)	(0.0105)	(0.00479)	(0.00755)
Firm × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.290	0.048	0.157	0.008	0.077	0.023	0.010
Observations	161,971	161,971	161,971	161,971	161,971	161,971	161,971

Table A.3

One-Year House Price Changes

This table repeats the analysis of Tables 2–4, redefining %Δ *House Price* to represent the zipcode level change in house prices from 2007 to 2008, rather than 2007 to 2012. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, 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	0.292***	0.230***	0.200***	0.0700***	0.237***	0.116***	0.213***
	(0.0534)	(0.0379)	(0.0305)	(0.0210)	(0.0445)	(0.0257)	(0.0355)
Pre-2008 Measure	0.789***	0.212***	0.416***	0.0756***	0.277***	0.123***	0.192***
	(0.0205)	(0.00894)	(0.0138)	(0.00431)	(0.0105)	(0.00478)	(0.00754)
Firm × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.290	0.048	0.157	0.008	0.077	0.023	0.010
Observations	161,989	161,989	161,989	161,989	161,989	161,989	161,989

Table A.4

One-Year House Price Changes and Excluding 2008-2009 Patents

This table repeats the analysis of Tables 2–4, redefining %Δ *House Price* to represent the zipcode level change in house prices from 2007 to 2008, and also excluding patents applied for in 2008-2009 from the outcome variables. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, 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	0.194***	0.179***	0.131***	0.0446***	0.141***	0.0831***	0.171***
	(0.0443)	(0.0337)	(0.0224)	(0.0158)	(0.0314)	(0.0210)	(0.0335)
Pre-2008 Measure	0.544***	0.161***	0.265***	0.0381***	0.145***	0.0785***	0.143***
	(0.0137)	(0.00769)	(0.0104)	(0.00305)	(0.00612)	(0.00452)	(0.00693)
Firm × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.223	0.033	0.112	0.004	0.044	0.013	0.006
Observations	161,989	161,989	161,989	161,989	161,989	161,989	161,989

Table A.5
Conditional on Continued Patenting

This table repeats the analysis of Tables 2–4, limiting the sample to inventors who did apply for a patent in the post-period (2008-2012). Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, 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	0.135***	0.105***	0.164***	0.0378*	0.162***	0.0427	-0.00552
	(0.0401)	(0.0384)	(0.0337)	(0.0218)	(0.0404)	(0.0285)	(0.0145)
Pre-Crisis Measure	0.558***	0.268***	0.431***	0.0984***	0.274***	0.179***	0.284***
	(0.0203)	(0.0130)	(0.0141)	(0.00691)	(0.0122)	(0.00789)	(0.0121)
Firm × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.272	0.061	0.151	0.009	0.069	0.030	0.067
Observations	81,080	81,080	81,080	81,080	81,080	81,080	81,080

Table A.7
Alternative House Prices Measure (Zillow)

This table repeats the analysis of Tables 2–4, using an alternative zipcode level price index from Zillow. Standard errors are clustered by firm and inventor residential zip code. *,**, 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	0.188***	0.129***	0.105***	0.0426***	0.162***	0.0665***	0.135***
	(0.0283)	(0.0224)	(0.0166)	(0.00956)	(0.0185)	(0.0140)	(0.0155)
Pre-2008 Measure	0.787***	0.213***	0.418***	0.0773***	0.278***	0.124***	0.193***
	(0.0198)	(0.00893)	(0.0143)	(0.00439)	(0.0105)	(0.00477)	(0.00781)
Firm × CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.290	0.048	0.159	0.008	0.078	0.023	0.011
Observations	153,169	153,169	153,169	153,169	153,169	153,169	153,169

B Model

B.1 Basic Setup

The model is a variant of the Holmström (1999) work on incentive provision through career concerns. 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 (H) and this information is private. However, conditional on knowing that they

Table A.6

Firm Size

This table repeats the analysis of Tables 2–4, successively limiting the sample to fims with less than 1000, 100, 50, 30 and 10 inventors in the sample, respectively. Standard errors appear in parentheses and are clustered by firm and inventor residential zipcode. *,**, 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
Less than 1000 inventors (N=138564)							
%Δ House Price Post	0.206***	0.173***	0.142***	0.0502***	0.179***	0.0886***	0.146***
	(0.0357)	(0.0275)	(0.0210)	(0.0138)	(0.0271)	(0.0183)	(0.0221)
Less than 100 inventors (N=87355)							
%Δ House Price Post	0.161***	0.151***	0.122***	0.0761***	0.156***	0.0833***	0.125***
	(0.0477)	(0.0375)	(0.0284)	(0.0221)	(0.0329)	(0.0249)	(0.0286)
Less than 50 inventors (N=71843)							
%Δ House Price Post	0.117**	0.149***	0.123***	0.0824***	0.150***	0.0733**	0.105***
	(0.0556)	(0.0457)	(0.0352)	(0.0280)	(0.0400)	(0.0290)	(0.0325)
Less than 30 inventors (N=61366)							
%Δ House Price Post	0.0835	0.147***	0.115***	0.0772**	0.119***	0.0833**	0.108***
	(0.0604)	(0.0512)	(0.0393)	(0.0338)	(0.0443)	(0.0337)	(0.0364)
Less than 10 inventors (N=43944)							
%Δ House Price Post	0.121	0.145**	0.117**	0.116**	0.162***	0.104**	0.119***
	(0.0741)	(0.0630)	(0.0494)	(0.0506)	(0.0570)	(0.0418)	(0.0459)

are not high quality, inventors do not know if they are of medium quality or low quality.[17] 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 $t = 0, 1, 2$. 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 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

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

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.[18] 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 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. As the following theorem shows, if the probability of success is sufficiently high, then high quality inventors always choose the exploratory task.

Theorem 1. *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.*

The proof is in the Appendix. To this basic setup, we now introduce housing market concerns.

B.2 Introducing Housing Net Worth Shocks

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 small shock such that their house price becomes $p_0^h > L$, and remain still with positive equity in the house, while a fraction $1 - \omega$ receive a more severe shock such that their house price becomes $p_0^l < L/(1+g)$ where $g > 0$, with negative equity. House prices are expected to appreciate by g percent following

[18] 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 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 lemma provides 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.

Lemma 2. *Suppose $\phi_M y_X + \phi_H \alpha y_E + \frac{(1-\alpha)\phi_H}{(1-\alpha)\phi_H + \phi_L}\alpha y_E < \pi$ and $\left(\phi_M + \phi_H + 1\right) y_X \geq \pi$. Then, in any equilibrium, the inventor will be forced to either sell or default if the exploratory task does not succeed. Moreover, in any equilibrium, a high quality inventor can avoid early liquidation and default by choosing exploitation.*

We now turn to investigating the impact of housing related concerns on equilibrium exploration by high quality inventors.

B.2.1 No Costly Default

Suppose that default itself is not costly. That is, we suppose $D = 0$. 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:

Theorem 3. *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 the significant drop in housing prices $\left(p_0^i = p_0^l\right)$ pursue exploration and those with smaller decline in housing prices $\left(p_0^i = p_0^h\right)$ pursue exploitation.

Intuitively, the inventors that experienced a more significant decline in housing prices are sufficiently underwater that they cannot hope to benefit from the expected recovery in housing prices. Even if house prices recover, their housing equity will remain at zero. Since default itself is not costly, this implies that their decision to pursue exploration is unimpacted by housing wealth concerns. Since $\alpha > \Delta$, the logic of Theorem 1 applies, guaranteeing that these inventors will always choose exploration. On the other hand, inventors with higher house prices do stand to gain from the expected recovery, which therefore introduces an additional cost to a failed exploration. Since such a failure will lead to a forced sale at time $t = 1$, the inventor may have to liquidate the house prior to the recovery, leading to lower wealth at the terminal date. This additional cost tends to incentive more conservative behavior and if the expected loss from an early liquidation, captured by $\gamma g p_0^h$, is sufficiently large, then the inventors with higher house prices will always choose exploitation. 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

B.2.2 Costly Default

There is empirical evidence, however, that foreclosure is costly for households. If the costs of default are sufficiently high, our results can flip.

Theorem 4. *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 that experienced a significant decline in housing prices $\left(p_0^i = p_0^l\right)$ pursue exploitation and those with a smaller decline in housing prices $\left(p_0^i = p_0^h\right)$ pursue exploration.

This result should not be surprising. Intuitively, when early liquidation concerns are relatively small but default itself is costly, it is those inventors who are underwater or with little positive housing equity (and thus close to default) who are unwilling to undertake risky innovation which may lead to foreclosure in the event of a failure.

B.2.3 Mental Stress and Cognitive Impairment

Given that default is costly, the prospect of default may also induce anxiety or mental stress. Furthermore, there is a body of empirical evidence which illustrates that stress can decrease the productivity of individuals at cognitively intensive tasks. We can model such cognitive impairment as a decrease in the probability of success. Let the probability of successful exploration be $\alpha^l < \alpha$ for high-quality inventors with low housing prices. We assume that inventors know if they are cognitively impaired or not. Therefore, as one would expect, inventors with low housing prices will choose exploitation if the the degree of cognitive impairment is sufficiently high, i.e. if α^l is sufficiently low. The proof is essentially identical to that of Theorem 4. A key distinction here, however, is that even if all inventors were to still choose exploration ex-ante, ex-post we would empirically see a difference in the exploratory output as a function of housing prices. Due to the cognitive impairment, inventors with low housing prices would be strictly worse at generating exploratory patents.

C Proofs

C.1 Proof of Theorem 1

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.*

C.2 Proof of Lemma 2

Proof. 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.* □

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.*

C.3 Proof of Theorem 3

Proof. Consider the incentives of high quality inventors whose house is initially valued at $p_0^l < L/(1+g)$. *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 price 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 investors 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:*

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

Recall that:

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

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.* □

C.4 Proof of Theorem 4

Proof. 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.* □