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Commuting and innovation: Are closer inventors more productive?☆

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A B S T R A C T

We estimate the causal effect of workplace–home commuting distance on inventor productivity. We construct a novel panel of U.S. inventors with precisely measured workplace–home distances and inventor-level productivity. Our identification strategy exploits firm office relocations as exogenous variation in the commuting distance of inventors at the firms. We find a significant negative effect from commuting distance on inventor productivity: every 10 km increase in distance is associated with a 5% decrease in patents per inventor–firm pair per year and an even greater 7% decrease in patent quality. The highest-performing inventors suffer more from increased commuting distance. We discuss the implications of our findings in the light of recent trends around telecommuting and remote work during the COVID-19 pandemic.

1. Introduction

An extensive body of ongoing research highlights the importance of understanding the spatial determinants of innovative productivity. Technology innovation is a vital source of economic growth (Romer, 1990) and critical for the performance of firms in high-technology industries (Hall et al., 2005). Recent work investigates the importance of spatial location or proximity on innovation, highlighting specific mechanisms like inter-inventor and inter-firm proximity (Breschi and Lenzi, 2016; Carlino and Kerr, 2015; Kim and Wu, 2019), housing markets (Bernstein et al., 2020), and regional policy design (Moretti and Wilson, 2017; Glaeser and Hausman, 2019).

Although this existing work documents important mechanisms particularly at the firm or patent level of analysis, there remains a gap in our understanding of how spatial considerations matter at the inventor and inventor–firm level of analysis. In particular, we study how commuting distance between an inventor's home and her workplace might affect the production of innovation by the inventor, and consequently, her firm. Relative to the existing studies of commuting in the literatures on urban economics and geography, this study addresses two gaps. First, we direct attention to understanding how commuting might affect inventors, a unique and important class of worker. Previous work focuses on commuting distance of general workers (e.g., Mulalic et al., 2014), and it remains unclear how commuting distance affects inventors. Second, we investigate how commuting affects individual-level productivity, an important outcome with little to no prior empirical study. Although the literature on commuting addresses important outcomes, such as wage compensation (Zax, 1991; Manning, 2003; Mulalic et al., 2014), residential mobility (Zax and Kain, 1996), and life quality (Kahneman and Krueger, 2006), a relatively limited set of work looks directly at individual-level performance, although some studies address absenteeism associated with long commutes (e.g., Van Ommeren and Gutiérrez-i Puigarnau, 2011).

Thus, we address the question: How do longer workplace–home commutes affect inventor productivity? Theoretically, it is unclear whether there will be a significant relationship in aggregate. On the one hand, a

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longer commute may adversely affect inventor productivity if inventors spend less time at work (Bloom et al., 2009), face a higher cost of providing effort (Shapiro and Stiglitz, 1984; Zenou, 2002; Ross and Zenou, 2008; Zenou, 2009), or engage in less in-person communication and collaboration to share knowledge (Battiston et al., 2020; Catalini, 2017; Jaffe et al., 1993). On the other hand, several mechanisms could also improve inventor productivity and offset these negative effects: inventors with longer commutes could receive higher efficiency wages (Ross and Zenou, 2008; Zenou, 2009), face less stress (Ashforth et al., 2000), and have more individual time to develop novel ideas (Furnham, 2000). Therefore, we must turn to the data to assess whether commuting distance has a significant causal effect on inventor productivity.

We construct a novel inventor–firm–year panel dataset of U.S. inventors that relates inventor productivity to precise measures of workplace–home distance. To measure inventor-level productivity, we leverage the rich information contained in patent records, which allow us to proxy the scientific and economic value generated by the inventors (Pakes, 1986; Hall et al., 2001). Patents serve as a meaningful indicator of the innovation and rents captured by both firms (Pakes, 1985; Kogan et al., 2017) and the inventors they employ (Toivanen and Väänänen, 2012; Kline et al., 2019). To measure commuting distance for each inventor, we combine the patent data with comprehensive firm establishment location data and inventor residential location data from housing transaction records.

Our empirical design seeks to overcome the identification challenge of residential sorting. Both inventors and firms make endogenous location choices based on factors such as housing costs, amenities, and of course commuting costs. To solve this endogeneity problem, we exploit firm relocations that exogenously shock commuting distance in a stacked and generalized difference-in-differences design. We adopt this methodology from Mulalic et al. (2014), where they use firm relocations as a quasi-experimental setting to investigate the impact of commuting distance on wage compensation. In our case, the identification strategy focuses on firm relocations that change the workplace–home commuting distance for inventors who retain the same home location and continue to work for the same firm before and after the relocation.

We find a 5% decrease in inventor productivity measured in raw annual patent counts for every 10 km increase in commuting distance. For patent quality as measured by citations, the effect is even larger with a 7% decrease in inventor productivity for every 10 km increase in commuting distance. The productivity loss is larger for the highest-performing inventors, those in the top 10% of all the inventors we study. The results are robust to a variety of alternative empirical tests that investigate and rule out other factors that may affect our measurement of the relationship between commuting distance and inventor productivity, i.e., firm relocations relative to pre-trends in inventor performance; firm-level characteristics, time-varying amenities, composition of the inventor sample, etc.

This study makes several contributions. First, we provide the first direct causal estimate of the impact of commuting on individual-level productivity in the literature, for a particular class of skilled workers: inventors. We measure a key implication of the commuting costs assumed in the monocentric city model (Alonso, 1964; Duranton and Puga, 2015; Mills, 1967; Muth, 1969), which should interest urban and economic geography scholars in general. The negative effect of longer commutes on inventor productivity acts against positive agglomerative forces that cause populous cities to be more productive, such as improved matching within a larger labor pool (Helsley and Strange, 1990; Lagos, 2000), increased specialization via division of labor (Baumgardner, 1988; Becker and Murphy, 1992; Duranton, 1998), and more knowledge spillovers (Jovanovic and Rob, 1989; Glaeser, 1999; Duranton and Puga, 2001).

Second, we contribute to recent literature studying the relationship between the spatial organization of inventors and firm innovation performance. Recent work continues to investigate the effect of spatial proximity on innovation (Aggarwal et al., 2020; Breschi and Lenzi, 2016; Carlino and Kerr, 2015; Roche, 2020) and the role of policy in that relationship (Moretti and Wilson, 2017; Glaeser and Hausman, 2019). We focus specifically on inventor–firm proximity, the dimension of proximity unexplored in prior work.

Finally, we apply the findings of this study to derive implications for future research on telecommuting and remote work. The research for this study largely took place prior to the COVID-19 pandemic, and telecommuting and remote work were not common in our study periods. That said, our findings relating innovation to physical commuting can provide insights towards an understanding of the relationship between innovation performance and telecommuting—both as a partial and full substitute for physical commuting. Nevertheless, significant open questions remain, particularly about how telecommuting relates to general productivity and creativity, which are both necessary components of innovation performance. We call for future research to tease out the specific mechanisms through which telecommuting might affect the innovation generated by high-skilled workers.

The rest of the paper is structured as follows. First, we describe the construction of the inventor–firm–year panel data sample central to this paper. Second, we discuss the key endogeneity considerations and present our empirical strategy leveraging workplace relocations for causal identification. Third, we document the empirical findings. We then conclude with a summary of our contributions and discuss opportunities for future work.

2. Data

Leveraging a novel combination of several data sources, we construct a unique inventor–firm–year panel for U.S. firms and inventors between 1997 and 2012. The data contains precise locations of both the workplace and home of inventors, allowing us to accurately construct various measures of workplace–home commuting distance for each inventor. Moreover, our setting of inventors lends itself directly to measuring individual-level contributions to firm productivity, through measures of patenting output that are linked to both the inventors and their employing firms. This data then allows us to exploit within-city relocations of the firm offices, serving as exogenous shocks to the workplace–home distance for each inventor.

2.1. Data construction

There are three different data types combined in this paper: patent data, employee data, and firm data. The U.S. Patent and Trademark Office (USPTO) data captures the whole universe of inventors and their firms in the U.S. Because the address information in the USPTO data is insufficiently precise for our desired analysis, we merge the inventors and firms from the USPTO data to DataQuick and InfoUSA data on inventor residences and firm establishments, respectively.

2.1.1. Employee data: Dataquick

To identify the residential location of inventors in our sample, we use detailed housing transactions data from DataQuick, a leading supplier of real estate data and analytics, to obtain the street address of the inventors.[1] The data covers 60 combined statistical areas (CSA) in 23 states from 1993 to 2012 and includes more than 195 million housing transactions and refinances.[2] For each transaction, we observe both the exact address of each home bought/sold, and the full name of the home buyers and sellers.

[1] DataQuick was acquired by CoreLogic in 2014.

[2] We use combined statistical areas (CSAs), instead of the metropolitan statistical areas (MSAs) that make up each CSA, because CSAs better reflect the possible intra-region commuting flows and economic ties. See Ferreira and Gyourko (2015) for additional information about the construction of the DataQuick sample. Table 1 provides further information about the geographic coverage of the sample.

Table 1
Data Composition by CSA. The Final Sample consists of inventors used in our main analyses, and All Inventors reflects the entire set of inventors in the USPTO data. The numbers represent observation counts of inventors and firms by CSA, and the percentages of inventors and firms in a CSA are shown in parentheses. The six largest CSAs by population are shown, ordered by the count of inventors, while the rest are grouped into Others.

Combined Statistical Area	Final Sample		All Inventors
	Inventors	Firms	Inventors
San Jose-San Francisco-Oakland	1168	341	146,631
(CA)	(34%)	(29%)	(26%)
Boston-Worcester-Providence	515	180	67,922
(MA-RI-NH-CT)	(15%)	(15%)	(12%)
Los Angeles-Long Beach	363	126	60,503
(CA)	(11%)	(11%)	(11%)
Chicago-Naperville	205	72	46,188
(IL-IN-WI)	(6%)	(6%)	(8%)
New York-Newark	160	92	84,529
(NY-NJ-CT-PA)	(5%)	(8%)	(15%)
Washington-Baltimore-Arlington	133	65	33,091
(DC-MD-VA-WV-PA)	(4%)	(6%)	(6%)
Others	901	304	124,117
	(26%)	(26%)	(22%)
Total	3445	1180	562,981
	(100%)	(100%)	(100%)

2.1.2. Firm data: InfoUSA

To identify the workplace location of inventors in our sample, we use historical firm establishment location data from InfoUSA containing the street addresses of offices of all firms in the US between 1997 and 2012. InfoUSA aggregates firm location data from various public sources, including yellow pages, credit card billing data, company annual reports, etc. InfoUSA also verifies information via phone calls and web research every year (DiNardo and Lee, 2004). The data provides information about firm name, street address, NAICS code, employee count, and sales volume. To verify the accuracy of InfoUSA data, we compare it to the County Business Patterns (CBP) data by state, and we find the totals to be quite similar.[3] The InfoUSA data covers more than 15 million verified firm establishments in U.S.

2.1.3. Matching across data

To construct a panel of matched inventor–firm pairs, we start with the inventor and firm information in the USPTO data between 1975 and 2012.[4] Li et al. (2014) provide a disambiguated patent database identifying unique inventors across patents and distinguishing inventors with identical or similar names. Each patent contains the names of the inventors, the firm (i.e., assignee) that owns the patent and most likely employs the inventor(s), and the home city and state of each inventor in the U.S. To complement the limited inventor location information in the USPTO data, we first match the USPTO inventor names and locations (city and state) with the DataQuick housing transaction data that reveals exact home addresses. We then match firm names and locations against the InfoUSA data to obtain precise firm establishment addresses. The matching process is described in detail in the paragraphs below.

To obtain inventor home addresses, we first match home buyer names exactly against inventor names from the same city. We then match inventor names to seller names in the subsequent transaction to obtain ownership years for each home buyer. To restrict our sample to owner-occupiers, we exclude cases where people with the same names own different addresses in the same city because we cannot identify their main residence or whether they are different people with the same name. In other words, we identify homeowners with unique names within a city.[5] Overall, we match around 264,000 inventors, or 47% of all inventors, to their exact home addresses. To assess the validity of this matching process, we conduct a balance test comparing the matched inventors with unmatched inventors in terms of their innovation performance: we find no statistically significant difference across these two groups.[6]

We then manually match USPTO firm names against firm establishment names in the firm location data to obtain inventor workplace addresses. We obtain precise office locations for 36,468 firms that applied for patents between 1997 to 2012 with inventors for whom we could identify their precise home address. To identify an inventor's precise work location if her employer has multiple establishments within the CSA, we select the most likely location based on whether it has by far the largest number of employees and whether it has a "research laboratory" designation in the corresponding NAICS codes.[7] We drop observations where it was impossible to uniquely identify a main office location within the CSA. This process results in 35,836 single-location firms.

As we describe later in our empirical strategy section, we use firm relocations as exogenous shocks to commuting distances. In service of this empirical strategy, we identify within-CSA business relocations where the main firm establishment location within the CSA changes from one year to the next. To improve the power of our estimates, we limit our sample to firms making substantial moves of more than one kilometer. We then identify inventors who worked (i.e., patented) for the relocating firm both before and after its relocation. Finally, we eliminate relocations that occurred in 1997 or after 2010, so we have data both before and after the relocation. We also exclude outliers that account for 3% of our total number of observations.[8]

Our study focuses on the inventors who changed neither their home locations nor their employers during the sample period. This restriction is required because of our identification strategy: we study only commuting distance changes from firm relocation, not from inventors moving homes or changing jobs. Among all the inventors who work at relocating firms, 50% of them change neither their home nor their job, and we focus on these inventors in our sample. There are other types of inventors, too: 46% of them move their residence; 11% of them change their job; and 7% of them change both their residence and their job. Our final sample consists of 22,917 inventor–firm–year observations and 3445 inventor–firm pairs, representing 3417 unique inventors employed at 1068 relocating firms.

2.2. Variables

2.2.1. Dependent variables: Inventor productivity

We construct several patent quantity and quality measures to capture inventor productivity based on the following rules. We attribute each patent as the output of the assigned firm and the listed inventor(s) based on its application year, which is the year when the invention was initially filed at the USPTO. We use patent application year rather than grant year because we are interested in when an inventor generates the invention, not when it is first recognized.[9] We only consider granted

[3] See Online Appendix A.1.2.

[4] We focus on utility patents, which account for more than 90% of all patents granted by the USPTO. The raw patent data covers 828,217 ultimately granted patents that were filed by 562,981 inventors living in the 60 CSAs.

[5] Although homeowner names are unique within our cleaned dataset, there could be multiple same-name individuals living in the same city who are not in our dataset. This measurement error potentially attenuates our estimates towards zero. As a robustness check, we estimate an alternative specification by weighting each inventor–firm pair inversely proportional to the probability of another person having the same name in the same city. The results are consistent with our main results. See Online Appendix A.2.

[6] See Online Appendix A.1.4.

[7] We only retain establishments that have five times more employees than all other establishments of the same firm in the CSA combined.

[8] See Online Appendix A.1.3.

[9] Given the time lag between patent application filings and USPTO decisions on whether to grant patents, the patent database is necessarily incomplete in the years leading up to 2012 since some patent applications had not yet been

patents, to ensure that the inventions satisfy a minimum quality threshold as determined by the USPTO.[10] Our patent quantity measure, *Patent Count*, is the number of annual granted patents to the focal inventor–firm, applied for in the focal year.

Nevertheless, granted patents do differ in importance and quality (Hall et al., 2005). To account for quality, we adopt standard measures used in the innovation literature (Hall et al., 2001; Bessen, 2008). *Scaled Citation* re-scales the total number of forward citations to patents by considering year and category fixed effects to control for mechanical differences in propensity to cite.[11] Citations proxy for a patent's scientific quality: the cited patent both conceptually forms part of existing knowledge that the citing patent builds upon and legally constitutes prior art that limits the applicability of claims in the citing patent. Trajtenberg (1990) provides empirical evidence that the number of citations represents value and novelty of innovation. Two other measures of patent scientific quality are *Generality* and *Originality* scores, introduced by Trajtenberg et al. (1997). *Generality* scores measure whether a patent is cited by subsequent patents from a wide range of technological categories, whereas *Originality* scores measure whether a patent cites many prior patents from different technological categories. These two measures represent innovation diversity. *Generality* represents whether a patent has a potential to be applied in various innovations. *Originality* indicates whether a patent uses a diverse mix of pre-existing innovations to achieve a unique invention.[12]

Beyond citation-based quality measures, we leverage patent maintenance fee data from 1980 to 2019 to build another measure of patent quality regarding market value, called *Payment Count*. We build on prior work by Pakes (1986) and Bessen (2008) that leverage this data. The USPTO website states that "maintenance fees are required to keep in force all utility and reissue utility patents based on applications filed on or after December 12, 1980." In short, to keep patents in force and valuable to the patent owner, patent owners pay maintenance fees 3.5, 7.5, and 11.5 years after the date of patent grant. Because the fee more than doubles for each subsequent renewal, we consecutively assume that the economic value of a patent is monotonically and positively related to the number of maintenance fee payments made. Hence, we use the number of maintenance fee payments, *Payment Count*, made by a firm to renew a patent as a measure of the patent's economic value. To avoid the truncation problems associated with newly granted patents, we adjust the raw number of payments by considering the conditional probability matrix.[13]

2.2.2. Main independent variable: Workplace–home distance

Using the panel of matched inventor–firm pairs, we measure commuting distance between an inventor's workplace and home, with our primary independent variable *Distance* reflecting the geodesic distance: the shortest path between two points on the curved surface of the Earth between inventor's workplace and home.[14] We use geodesic distance as our main measure of commuting distance because it is parsimonious and fixed over time.[15]

Table 2
Pre- and Post-Relocation Summary Statistics. Summary statistics at the inventor–firm level. The results are based on 3445 unique inventor–firm pairs used in our main analyses and compare their average values before firm relocations (i.e., Pre-Relocation) and after relocations (i.e., Post-Relocation). *Distance* is in kilometers.

	Mean	Std. Dev.	Min	Median	Max
Pre-Relocation					
Patent Count	0.858	0.879	0.000	0.600	8.333
Scaled Citation	1.365	2.561	0.000	0.491	30.892
Generality	0.399	0.495	0.000	0.250	4.340
Originality	0.206	0.331	0.000	0.087	4.775
Payment Count	1.816	2.085	0.000	1.312	15.333
Distance	21.456	16.166	0.000	17.184	98.813
Post-Relocation					
Patent Count	0.328	0.654	0.000	0.000	9.000
Scaled Citation	0.633	2.463	0.000	0.000	81.801
Generality	0.128	0.334	0.000	0.000	6.362
Originality	0.079	0.212	0.000	0.000	3.802
Payment Count	0.589	1.300	0.000	0.000	23.611
Distance	21.607	15.919	0.001	17.463	99.908

2.3. Descriptive analysis

2.3.1. Geographic distribution

Fig. 1 shows the distribution of workplace–home *Distance*. The distribution skews towards shorter commutes, and its mode is around 10 km with substantially fewer observations at greater distances. The majority of inventors in our sample have a commuting distance of less than 18km. This distribution is consistent with studies by the U.S. Department of Transportation (e.g., U.S. Government Bureau of Transportation Statistics, 2003), suggesting that the matching process generated sensible workplaces-home matches for the inventors.

Table 1 shows the distribution of our observations between CSAs, focusing on the six largest CSAs by total population. Roughly a third of all inventor–firm pairs in our sample are from the San Jose-San Francisco Bay (CA) area, representing Silicon Valley and the presumed heart of the U.S. technology industry. The proportion of Silicon Valley in our sample is similar to its portion in the universe of inventors filing with the USPTO, suggesting that the geographic distribution of our matched inventors is comparable to the distribution of all U.S. inventors.

2.3.2. Summary statistics: Pre- and post-relocation

Table 2 shows summary statistics for our final sample at the inventor–firm pair level, taking the pre- and post-relocation averages. In both periods, the mean values of productivity measures are well above their median values. This finding suggests that patent outcomes in our sample are skewed with a long tail of very productive inventors, consistent with prior literature (e.g., Akcigit et al., 2016).

granted. Assuming that the USPTO's idiosyncratic time lag is consistent within-industry, this sampling consideration should impact inventors working in the same business establishment equally and not bias our estimation results.

[10] In an investigation of patent applications filed between 1996 and 2005, Carley et al. (2015) find that around 55% of all patent applications are eventually granted, suggesting that granted patents do satisfy some minimum quality threshold.

[11] Trajtenberg et al. (1997) document this adjustment process as a way to "re-scale" citations, and this motivates the variable name, *Scaled Citation*. This variable is also used by Bernstein (2015). The citation information is originally at the patent level. Because our final data is at the inventor–firm–year level, we average *Scaled Citation* by each inventor–firm pair at a given year. This conversion method applies to all the other quality measures.

[12] Mathematically, *Generality* for patent i is:

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

where s_{ij} is the share of citations received by patent i that belong to patent category j, out of n_j patent categories. *Originality* is defined similarly, except that it uses citations made by patent i to patent categories j.

[13] Online Appendix A.4 details the construction of the *Payment Count* variable.

[14] We use Vincenty (1975) equations for a mathematical model of the Earth.

[15] We also create two other commuting distance measures based on the assumption that the inventor might be driving or taking public transit to work. *Drive Distance* is the shortest route for a motor vehicle, i.e., via roads that are legal to drive on, between the inventor's home and workplace. *Drive Duration* is the estimated fastest time it takes to drive or take public transit between the inventor's home and workplace, accounting for speed limits and historical traffic conditions. Along with the main measure *Distance*, these three commuting distance measures are highly correlated (i.e., correlations are greater than 0.9), and the regression estimates based on *Drive Distance* and *Drive Duration* are consistent with the main results based on *Distance*. See Online Appendix A.7.6.

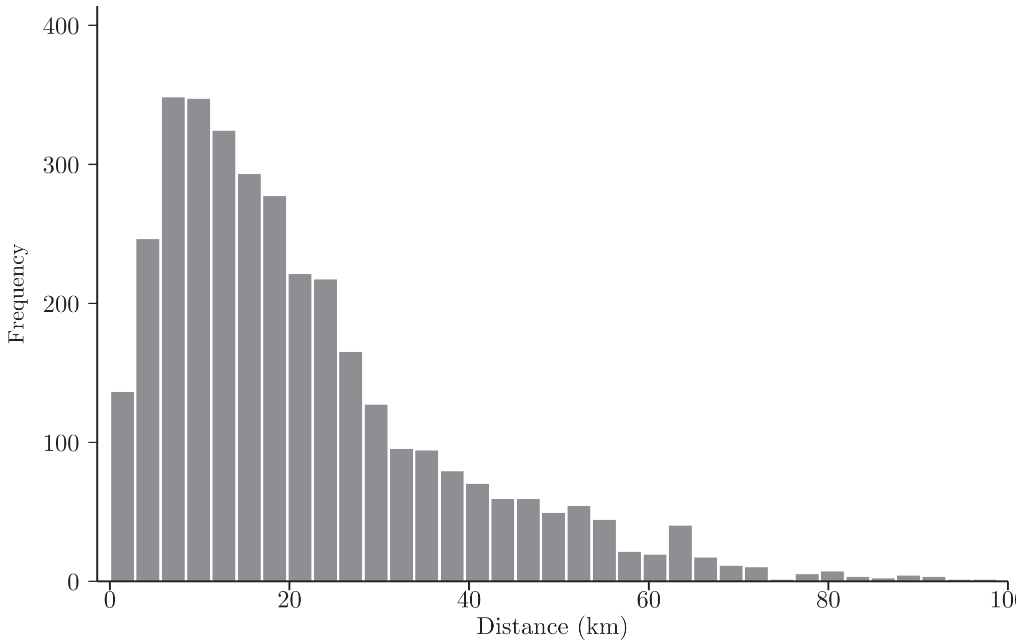

Fig. 1. Distribution of Workplace-Home Distance. Frequency distribution at the inventor–firm level. The variable *Distance* represents geodesic distance in kilometers (km) between workplace and home prior to firm relocations.

We also find that all the inventor productivity measures decline after firm relocation. While some of this decline in productivity post-relocation is due to truncation bias stemming from the application-grant time lag of patents, some might be genuine and related to the relocation itself. On the other hand, the mean commuting distance remains roughly constant after relocation, and this shows that the relocation-driven positive and negative distance shocks are generally comparable. Hence, we find a discrepancy that the overall productivity measures decline even though the overall distance remains unchanged. This discrepancy implies that the negative distance shock has a stronger impact on productivity than the positive shock does.[16]

2.3.3. Balance test

Table 3 reports the balance test results for inventor–firm–year observations prior to a workplace relocation event, divided by the direction of the commuting distance shock. Columns (4–6) show the results of two-sample *t*-tests for equality of means between these three groups. Prior to the workplace relocation, inventors in the closer and farther groups have statistically indistinguishable productivity in most cases. Unsurprisingly, these two groups differ significantly in terms of workplace–home *Distance*: inventors who live closer to the workplace are mechanically more likely to experience an increase in their workplace–home *Distance* than for inventors who previously lived farther away. Table 3 shows that *Inventor Pre-Relocation Income* is somewhat higher for the farther group than for the closer group.[17]

The systematic differences in *Inventor Pre-Relocation Income* need to be addressed. After further investigation, we find that these differences can be explained by two facts acting together. First, the average establishment tends to be moving away from city center, with the average move being 2.55 km away. Second, higher-income and more-productive inventors preferentially live in suburb areas: Fig. 2 plots average *Patent Count* and *Inventor Pre-Relocation Income* against distance from home to the central city. Therefore, inventors whose firm on average moves towards their home are more likely to live in the suburbs, and they tend to have higher *Inventor Pre-Relocation Income* than inventors whose firm on average moves away from their home. Our identification strategy alleviates this concern by including inventor–firm fixed effects to absorb time-invariant differences between inventors.

2.3.4. Non-parametric estimation

Fig. 3 presents a non-parametric estimation of our main research question, relating workplace–home *Distance* with *Patent Count* without controlling for anything. Using the full sample of 3445 matched inventor–firm pairs, Fig. 3 shows a clear negative correlation between distance and productivity. The patenting rate declines approximately linearly and steadily with increasing workplace–home distance.

This negative correlation does not yet imply any causal relationship since endogenous sorting of inventors and firms potentially confounds the basic observed relationship. The next section details the empirical strategy for causal identification in light of these possible confounding effects.

3. Empirical design

We first motivate the need for our identification strategy by discussing the main issue of endogenous sorting. We then describe our methods and assumptions, particularly with respect to the labor market.

3.1. Endogeneity: Residential sorting

For estimating the causal effect of commuting distance on inventor productivity, the main challenge is that the location choices of

[16] Online Appendix A.7.2 further investigates this heterogeneity.

[17] We obtain limited income information by matching housing transactions against loan application data in the Home Mortgage Disclosure Act files, as described in Ferreira and Gyourko (2015). Our income data consists of gross wage and some additional non-labor income, such as interests and dividends. We only observe pre-relocation income data: inventor income is revealed when an inventor makes a housing transaction, but we study the inventors who do not change their home. Those inventors, by definition, make housing transactions only before relocation.

Table 3
Balance Test by Direction of Distance Shocks. Summary statistics at the inventor–firm level. Pre-relocation means are provided with standard errors in parentheses and number of inventor–firm pairs in brackets. Closer/Same/Farther columns indicate subsamples for which commuting distance decreased by more than 1 km, stayed the same (i.e., changed by less than 1 km), and increased by more than 1 km, respectively. *Distance* is in kilometers, and *Inventor Pre-Relocation Income* is in 1,000 U.S. dollars.

	(1)	(2)	(3)	*p*-value		
	Closer	Same	Farther	(1) vs. (3)	(1) vs. (2)	(2) vs. (3)
Patent Count	0.850	0.846	0.869	0.547	0.928	0.591
	(0.024)	(0.036)	(0.023)			
	[1348]	[528]	[1569]			
Scaled Citation	1.380	1.272	1.383	0.970	0.415	0.372
	(0.073)	(0.098)	(0.064)			
	[1348]	[529]	[1569]			
Generality	0.391	0.415	0.401	0.598	0.333	0.563
	(0.013)	(0.022)	(0.013)			
	[1348]	[529]	[1569]			
Originality	0.193	0.195	0.220	0.028	0.899	0.141
	(0.008)	(0.013)	(0.009)			
	[1348]	[529]	[1569]			
Payment Count	1.808	1.817	1.823	0.854	0.937	0.956
	(0.057)	(0.089)	(0.052)			
	[1348]	[529]	[1569]			
Distance	26.47	19.38	17.85	0.000	0.000	0.041
	(0.046)	(0.067)	(0.037)			
	[1348]	[529]	[1569]			
Inventor Pre-Relocation Income	131.881	130.837	118.807	0.035	0.918	0.026
	(6.011)	(5.281)	(2.569)			
	[599]	[239]	[711]			

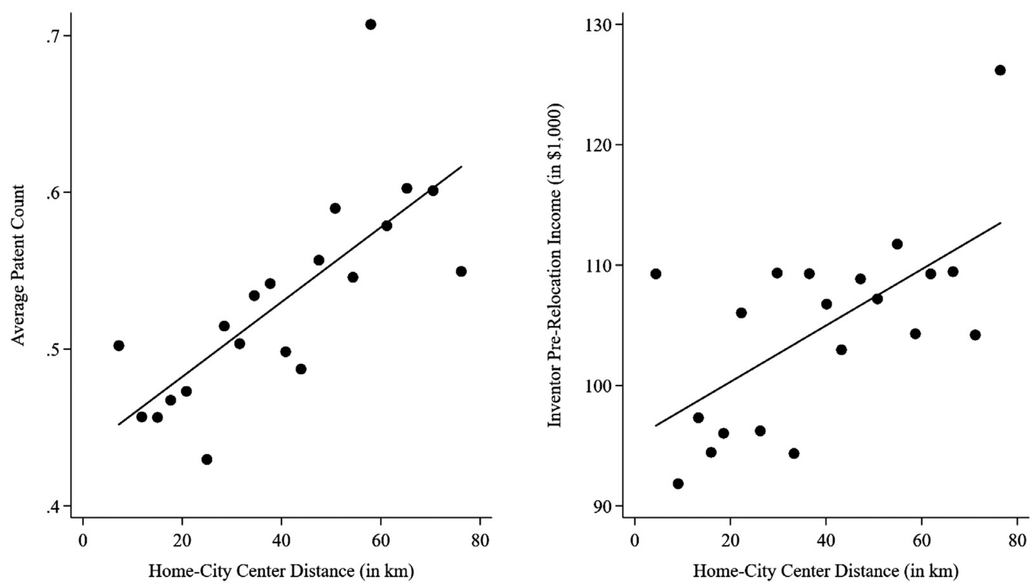

Fig. 2. Residential Sorting by Distance to City Center. Binned scatter plots at the inventor level. The horizontal axes denote an inventor's home-central city distance (in km), which is fixed over time because the main sample consists of the inventors who did not move their home locations. The vertical axis in the left graph denotes the average number of patents granted to an inventor (i.e., Average *Patent Count*) and in the right graph measures an inventor's income before firm relocations (i.e., *Inventor Pre-Relocation Income*). Bins are formed for each nearest 5 km.

both inventors and firms are endogenously determined. Inventors endogenously choose their place of residence based on a long list of factors in addition to commuting costs (Deitz, 1998), including amenities (Diamond, 2016) and price of homes (Dubin and Sung, 1987). Factors that firms consider in their office location decision include office rent and nearby productive amenities, in addition to geographic accessibility. Therefore, a simple regression of inventor productivity on commuting distance would be biased due to sorting.

We first consider the endogenous location decision of inventors motivated by the classic monocentric city model. The classic model consists of rich and poor households, and their income difference makes the rich demand more/larger housing than the poor under the same housing price. This mechanism results in residential sorting where the rich live in the suburbs, and the poor are in the city center (e.g., Brueckner, 2001).[18]

[18] While this model implies a positive correlation between income and distance to the city center, i.e., the assumed commuting distance, Gutiérrez-i Puigarnau et al. (2016) find a *negative* causal relationship between income on commuting distance in a study of workers in Denmark, despite an observed positive correlation between income and commuting distance documented in other empirical studies. Nevertheless, there are important contextual differences between the United States, the context for our study, and European countries (Brueckner et al., 1999), which could result in a different pattern for the correlational and causal relationships between income and commuting distance.

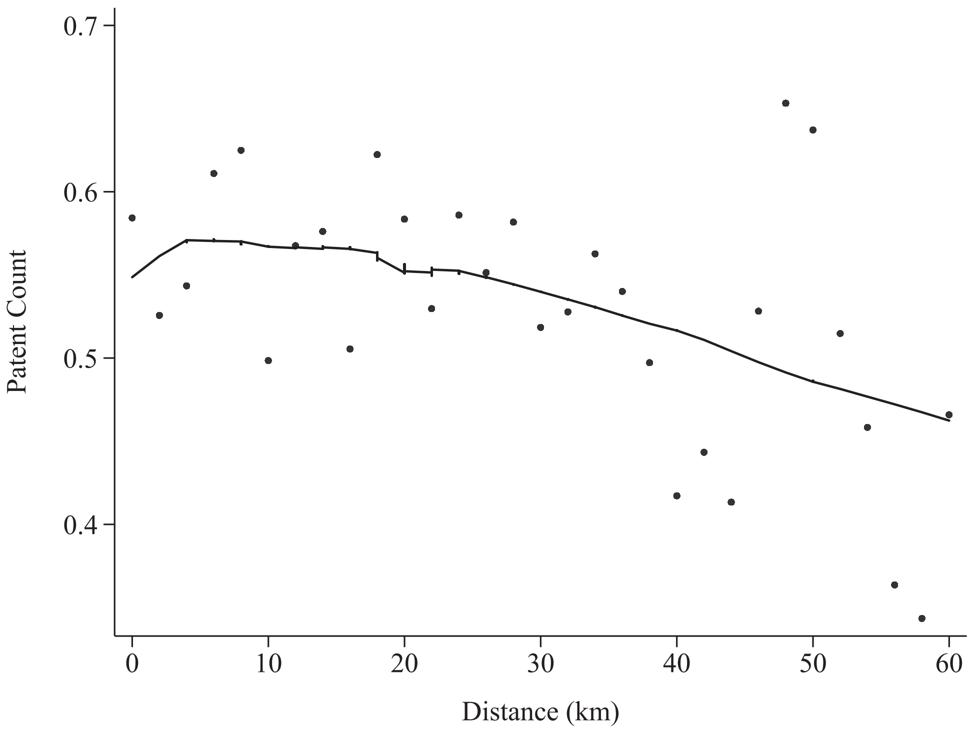

Fig. 3. Descriptive Relationship Between Workplace-Home Distance and Patent Count. Binned scatter plots at the inventor–year level. Both horizontal and vertical axes represent values prior to firm relocations. Bins are formed for each nearest 1 km.

Our model mirrors the standard monocentric model by distinguishing inventors by skill (i.e., high- and low-skilled) and using the income difference between high- and low-skilled inventors. In addition, knowledge workers tend to reside in the suburbs due to their stronger preferences for schools and children's education (Frenkel et al., 2013), whereas young college graduates who are relatively less-skilled prefer living close to the city center because of better labor market opportunities (Van Vuuren, 2018) facilitated by a labor market network based on residential proximity (Hellerstein et al., 2011). Thus, we assume a certain case of inventor sorting where high-skilled inventors reside in outlying suburbs, and low-skilled inventors live close to the center.[19]

We now demonstrate how the inventor sorting brings about a biased term in the estimation to measure the impact of commuting distance on productivity. Consider an inventor i working for firm j, living at a distance d_{ij} from the firm. Assume perfectly competitive labor markets where inventors are paid their marginal productivity of labor. For inventors heterogeneous in their productivity type θ_i, inventor productivity l_{ij} is determined by the following equation:

$$l_{ij} = \theta_{ij} + \beta_i d_{ij} + \delta_j \tag{2}$$

where θ_{ij} is an inventor–firm commuting distance-invariant productivity parameter that denotes the quality of the inventor–firm match, β_i is a measure of how distance affects individual-specific productivity, and δ_j is a firm-specific distance-invariant productivity parameter. This formulation allows for time-invariant heterogeneous distance effects across both inventors and firms, i.e., the two parameters differ by each inventor and each firm. We model inventor sorting by skill level and home-to-city center distance. For each city m, let x_{mi} be distance between inventor i's home and the center of m. Then, inventor–firm specific productivity parameters are drawn from the real interval such that the distribution of individual types is determined by:

$$\theta_{ij} = \alpha_0 + \alpha_1 x_{mi} + \epsilon_{ij} \tag{3}$$

where $\alpha_1 > 0$ due to inventor sorting, i.e., more productive inventors live farther from the city center, α_0 is a constant, ϵ_{ij} is a commuting distance-invariant match quality term, and $E(x_{mi}\epsilon_{ij}) = 0$. Thus, there is sorting in city m of inventor types according to distance from the city center. If the firm is located at the center of the city, then $x_{mi} = d_{ij}$. Assume that firms tend to be located closer to the city centers than homes, with a positive correlation between x_{mi} and d_{ij} on average. In this case, inventor i's distance to the city center correlates with distance to the firm, with $x_{mi} = \gamma_i d_{ij} + \mu_{ij}$, where $\gamma_i > 0$. Plugging this expression into Eq. 3 combined with Eq. 2, we have:

$$l_{ij} = \alpha_0 + (\beta_i + \alpha_1 \gamma_i) d_{ij} + \delta_j + \alpha_1 \mu_{ij} + \epsilon_{ij}. \tag{4}$$

Thus, the OLS estimate of β_i using Eq. 2 would be biased if $\alpha_1 > 0$ due to inventor sorting and if $\gamma_i > 0$ due to firms concentrating in a city center away from inventor residential locations.

3.2. Identification strategy

We address potential endogeneity by using firm relocations as exogenous shocks to commuting distance.[20] Fig. 4 shows the distribution of distance changes due to firm relocations: we observe large variation in the distance changes with a number of inventors who experience a distance shock of more than 10 km.

The crucial assumption for this identification strategy is imperfect inventor resorting after firm relocations, due to factors like home moving costs and heterogenous match quality between inventors and firms. In other words, some inventors prefer to stay at their home and with their employer even after a distance shock because their moving and job searching costs are greater than the benefits from resorting to an

[19] On the other hand, high-skilled inventors may choose to live closer to the center because they have higher time costs of commuting, which would induce a bias in the opposite direction. Regardless of the direction, our identification strategy eliminates the confounding effects in inventor sorting. In addition, Online Appendix A.3 modifies this inventor sorting model by focusing only on skill differences between inventors without economic considerations such as income and amenities.

[20] Neumark et al. (2006) note that state or local policies are rarely aimed directly at attracting relocating businesses but do exist on a case-by-case basis. Nevertheless, the design of our main data sample tends to exclude any of these situations.

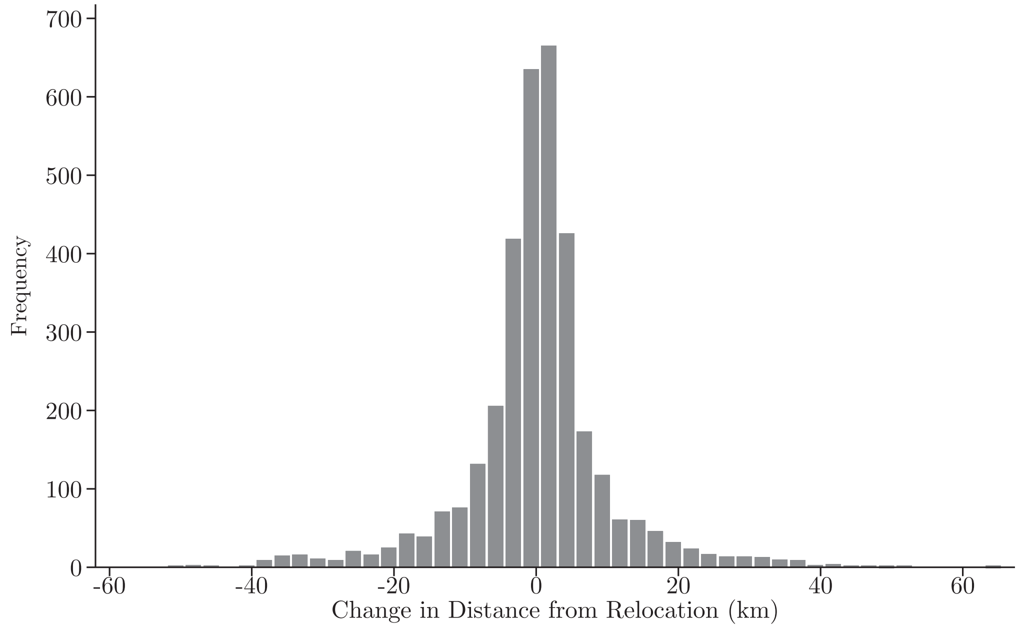

Fig. 4. Distribution of Workplace-Home Distance Changes. Frequency distribution at the inventor–firm level. The horizontal axis indicates the difference before and after firm relocations in geodesic distance between workplace and home (in km).

alternative home or employer.[21] For example, Teradyne Inc., a major high-tech producer of electronic component test equipment, moved its headquarters from Boston, MA to North Reading, MA in 2006. There are 10 inventors we identify as working with the company both before and after the relocation, and they did not move their residential location. Thus, they experienced changes in commuting distance solely due to the relocation. This *within–inventor–firm* but *across-time* variation in workplace–home distance lies at the core of our identification strategy. The measured average effect in this sample may be a lower bound for the population-level effect because an inventor who moves her home location or changes her job is more likely to be sensitive to change in commuting distance than an inventor who changes neither her home nor job. Section 4.3 further documents this effect.

With this particular sample, we estimate a difference-in-differences-style regression model to investigate how changes in commuting distance affect inventor productivity. Inventor–firm pair fixed effects and year fixed effects are included so that firm relocations are the only source of commuting distance change in the within–inventor–firm analysis. The precise specification for inventor i, firm j, and year t is as follows:

$$Y_{ijt} = \beta d_{ijt} + \alpha_{ij} + \gamma_t + \delta_{jt} + \epsilon_{ijt} \tag{5}$$

where Y_{ijt} is the dependent variable for inventor productivity regarding patenting for individual i working for firm j in year t. d_{ijt} is the distance between inventor i's home and firm j's office in year t. α_{ij} is an inventor–firm fixed effect that controls for the inherent productivity differences between individuals, taking into account the matching quality between inventor and firm. γ_t absorbs year fixed effects. δ_{jt} controls for firm location fixed effects before and after relocation at the ZIP code level. The firm location fixed effects account for potential differences in time-invariant productive amenities near the office before and after relocations; for example, a different set of nearby firms may provide different knowledge spillovers. ϵ_{ijt} is the error term. We cluster robust standard errors at the inventor–firm pair level.

[21] Aggregate job stability in the United States has remained relatively consistent over time (Diebold et al., 1997; Neumark et al., 1999).

The identification strategy assumes that there are no other events that occur simultaneously with firm relocations.[22] Correlated events may differently affect the productivity of inventors whose commuting distance increases versus those whose commuting distance decreases. However, the balance test results in Table 3 in Section 2.3.3 show that inventors who received a positive distance shock are not significantly different from inventors who received a negative distance shock in terms of patent productivity. Section 4.2.2 provides additional tests that account for time-varying firm characteristics.

3.3. *Imperfect labor market*

The interpretation of our estimated coefficients differs depending on labor market assumptions. In our base econometric model, we assume perfectly competitive labor markets where inventors are paid their marginal productivity of labor. In this case, if inventor wage does not depend on commuting distance beyond the direct impact that commuting has on productivity, we estimate the "pure" causal effect of commuting on inventor productivity.

However, in imperfect urban labor markets, firms have market power and pay inventors a wage below their marginal productivity. They may also compensate inventors for longer commutes by paying a higher wage. This wage compensation for longer commutes would incentivize these inventors facing longer commutes to stay at the firm and provide more effort (Zax, 1991). Mulalic et al. (2014) empirically find evidence of commuting-based wage compensation in Denmark.

If we assume that firms adjust wage compensation for inventor commutes to provide an efficiency wage and incentivize effort (Ross and Zenou, 2008), then our results can be interpreted as a total effect: our estimates combine the "pure" causal effect of commuting on productivity and the countering effect of a higher efficiency wage. Even for inventors who remain at the same home and the same job, our estimates

[22] Although we assume that there is no simultaneous event confounding the identification strategy, a firm could make a relocation decision partly based on the past performance of its inventors. Online Appendix A.5 investigates whether firms relocate endogenously towards better-performing inventors. We do not find any evidence that firms relocate in this way.

Table 4
Effect of Commuting on Inventor Productivity—Quantity. Fixed-effects OLS regressions at the inventor–firm–year level. Dependent variable *Patent Count* is the count of granted patents for an inventor–firm per year. Independent variable *Distance* is geodesic distance between workplace and home (in 10 km). Robust standard errors clustered at the inventor–firm level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.V.: Patent Count	(1)	(2)	(3)	(4)
Distance	-0.013*	-0.039**	-0.030**	-0.041**
	(0.007)	(0.016)	(0.014)	(0.019)
Inventor–Firm FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Firm Location FE	No	No	No	Yes
R^2	0.000	0.335	0.386	0.415
Inventor–Firm Count	3445	3445	3445	3445
Observations	22,917	22,917	22,917	22,917

represent a lower bound for the “pure” effect of commuting on inventor productivity, when taking into account this type of wage compensation.

We consider wage compensation in an imperfect labor market and investigate how this consideration changes our empirical model. In an imperfect urban labor market, firms have monopsony power over wages due to the limited number of jobs available in a certain geographic area (e.g., Manning, 2003). Assume that firms pay inventors an efficiency wage with longer commuting distance to discourage them from shirking (Ross and Zenou, 2008). We define a simplified wage equation as follows:

$$w_{ij} = w_{ij}^{m} + ew_{ij}d_{ij}$$

where w_{ij}^{m} is the market-clearing wage and ew_{ij} is the per-unit commuting distance efficiency wage that firm j pays to inventor i. Because only the excess wage beyond the market-clearing level can affect productivity by preventing inventors from shirking, inventor productivity then becomes:

$$l_{ij} = \theta_{ij} + (\beta_i + ew_{ij})d_{ij}.$$

Then, Eq. 4 in Section 3.1 becomes:

$$l_{ij} = \alpha_0 + (\beta_i + ew_{ij} + \alpha_1\gamma_i)d_{ij} + \delta_j + \alpha_1\mu_{ij} + \epsilon_{ij}.$$

In this case of imperfect labor markets, the existence of non-zero job search cost acts in conjunction with the existence of infra-marginal inventors due to heterogeneity in inventor–firm match quality ϵ_{ij} to keep some inventors from moving to a different job after firm relocation. Just as before, positive moving costs keep some inventors from moving to a different residential location. Looking at this subsample of inventors who do not re-sort, we subtract their productivity before and after the move to get:

$$\Delta l_{ij} = (\beta_i + ew_{ij})\Delta d_{ij}.$$

Given that ew_{ij} should always be the opposite sign of β_i, this implies that our estimates represent a lower bound for the weighted “pure” effect of commuting distance on inventor productivity.

4. Results

We first present the main results on outcomes of patent quantity and quality. We then explore heterogeneous effects for the highest-performing inventors. Finally, we show that the main results are robust to alternative specifications.

4.1. Main results

4.1.1. Patenting quantity

Table 4 shows estimated coefficients for our main difference-in-differences specifications. Column (1) shows that *Distance* is negatively correlated with *Patent Count*, as expected given the negative slope in Fig. 3. The size of the coefficient, however, triples after controlling for inventor–firm fixed effects in Column (2) and becomes more statistically significant. The difference between Columns (1) and (2) suggests that more-skilled inventors endogenously choose residential locations farther away from their workplace than less-skilled inventors, which biases the OLS coefficient in Column (1) downward.[23]

The result remains highly significant when we control for year fixed effects in Column (3) and firm location fixed effects in Column (4), suggesting that endogenous location choice by firms in pursuit of higher time-invariant productive amenities is not driving our results. Column (4) represents our preferred specification, with every 10 km increase in *Distance* causing an average decrease in inventor productivity of 0.041 patents per year. In percentage terms, this represents a 5% decrease in inventor productivity per 10 km, compared with the average 0.86 patents per year per inventor–firm pair before the move.

4.1.2. Patenting quality

Turning to measures of patent quality, we find the same negative effect of commuting distance on inventor productivity. Column (1) in Table 5 shows that a 10 km increase in commuting distance causes a 0.094 decrease in *Scaled Citations*, roughly 7% of the pre-relocation mean. This suggests that the decrease in *Patent Count* is not driven by inventors applying for fewer patents but by applying for more-impactful patents. The results for *Generality* and *Originality* in Columns (2) and (3) are consistent with this interpretation: the overall scientific quality measures fall with increasing commuting distance, in step with *Patent Count*. Testing for patent economic value proxied by the maintenance fee payments, *Payment Count*, shows a potential decrease. Although the coefficient is not statistically significant, it is likely due to the lack of power in this specification; the last maintenance fee payment is only required 11.5 years after the patent grant date, resulting in severe data truncation.

4.1.3. Inventor heterogeneity

We explore suggestive evidence for potential underlying mechanisms driving our results by investigating heterogeneous effects of commuting distance on inventor productivity. Given that highest-performing inventors may have a disproportionate impact on a firm's innovation output (e.g., Akcigit et al., 2016), we test whether the commuting distance effect is driven by these outstanding inventors. *Top Inventor* takes a value of 1 for inventors whose cumulative number of granted patents rank in the top 10% of our sample, and 0 otherwise. We include the interaction term, *Distance* × *Top Inventors*, to estimate the heterogeneous effect.

Table 6 shows that the negative effect of distance on inventor productivity is largely driven by the highest-performing inventors. Column (1) shows that *Patent Count* of the highest-performing inventors decreases by 0.159 more patents per year per 10 km than the other 90% of less-productive inventors, whose coefficient is reduced to a statistically insignificant 0.026 patents per year per 10 km. This large discrepancy is replicated with the two main patent quality measures, *Scaled Citation* and *Payment Count*, in Columns (2) and (3) respectively.[24]

To further investigate the heterogeneous effects, we consider a difference in mean productivity between *Top Inventors* and average inventors. Because mean productivity is higher for *Top Inventors*, their opportunity cost for every work hour lost to their commute would also be higher. However, even after taking their higher mean into account, *Top Inventors* still suffer more proportionally than the average inventor: a

[23] We confirm this by plotting pre-relocation inventor income and home price against commuting distance. We find a strong positive correlation between the two.

[24] Hereafter, we use *Patent Count, Scaled Citation*, and *Payment Count* as the three main innovation measures. *Patent Count* intends to measure the quantity of innovation, whereas *Scaled Citation* intends to captures innovation quality through the intellectual influence of patents on future inventions. *Payment Count* serves as a proxy for the economic value of patented innovations.

Table 5

Effect of Commuting on Inventor Productivity—Quality. Fixed-effects OLS regressions at the inventor–firm–year level. *Scaled Citation* re-scales the total number of forward citations to patents per inventor–firm pair per year by considering year and category fixed effects. *Generality* scores measure whether a patent is cited by subsequent patents from a wide range of technological categories per inventor–firm pair per year. *Originality* scores measure whether a patent cites many prior patents from different technological categories per inventor–firm pair per year. *Payment Count* calculates the number of maintenance fee payments made by a firm per inventor–firm pair per year. Independent variable *Distance* is geodesic distance between workplace and home measured in 10 km. Robust standard errors clustered at the inventor–firm level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.V.:	(1) Scaled Citation	(2) Generality	(3) Originality	(4) Payment Count
Distance	-0.094*	-0.025**	-0.013**	-0.047
	(0.049)	(0.011)	(0.006)	(0.042)
Mean of D.V. (Pre-Relocation)	1.365	0.399	0.206	1.684
Inventor–Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm Location FE	Yes	Yes	Yes	Yes
R^2	0.381	0.387	0.392	0.417
Inventor–Firm Count	3445	3445	3445	3445
Observations	22,863	22,863	22,863	22,863

Table 6

Effect of Commuting on Inventor Productivity—Top Inventor. Fixed-effects OLS regressions at the inventor–firm–year level. Top Inventor indicates inventors in the top decile in terms of average patent count. Robust standard errors clustered at the inventor–firm level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.V.:	(1) Patent Count	(2) Scaled Citation	(3) Payment Count
Distance	-0.026	-0.057	-0.018
	(0.019)	(0.048)	(0.041)
Distance × Top Inventor	-0.159**	-0.407**	-0.314**
	(0.073)	(0.172)	(0.149)
Mean of D.V. (Pre-Relocation): Ordinary Inventors	0.781	1.264	1.533
Mean of D.V. (Pre-Relocation): Top Inventors	1.670	2.421	3.276
Inventor–Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm Location FE	Yes	Yes	Yes
R^2	0.416	0.381	0.418
Inventor–Firm Count	3445	3445	3445
Observations	22,863	22,863	22,863

10 km increase in *Distance* causes a 10% drop in productivity, versus less than 4% for less-productive inventors. This finding suggests that there is a moderating mechanism driving stronger distance effects to the highest-performing inventors. For example, the cost of effort could increase more steeply with commuting distance for the top versus the average inventors.

4.2. Robustness checks

4.2.1. Pre-trend of inventor performance

One of the underlying assumptions in our inventor sample is that inventor performance is not correlated with the direction of a commuting distance change resulting from a firm relocation. To validate this assumption, we evaluate whether there are parallel pre-trends (prior to firm relocation) in innovation performance between the inventors experiencing positive distance shocks (i.e., farther commute group) and the others (i.e., closer or same commute groups). We adopt the standard test for parallel trends by estimating a generalized difference-in-differences specification that looks at yearly average of *Patent Count* by direction of distance shock. We estimate the following equation for inventor i, firm j, year relative to workplace relocation event y, and year t:

$$Y_{ijyt} = \beta_{ity}^{Farther} Farther\ Commute_{it} * \eta_y + \alpha_{ij} + \eta_y + \gamma_t + \delta_{jt} + \epsilon_{ijt} \tag{6}$$

where $Farther\ Commute_{it}$ equals 1 for inventor–firm pairs for whom the workplace relocation increased the workplace–home geodesic distance by 1 km or more, and 0 otherwise. η_y is an elapsed year fixed effect taking the value of 1 for the year $y \in [-4, 5]$ relative to workplace relocation event, and 0 otherwise. α_{ij} is an inventor–firm fixed effect, γ_t is a year fixed effect, and δ_{jt} is a firm location fixed effect.

Fig. 5 shows the estimated coefficients of $\beta_{ity}^{Farther}$ from Eq. 6. We do not observe any upward (downward) pre-relocation trends for the inventors who experience closer (farther) commuting distance due to relocation.[25] Furthermore, productivity for inventors with farther distance after relocation falls during the year of the relocation and afterwards remains lower relative to the productivity of those with closer distance. These findings confirm the assumption that inventor innovation performance does not depend on the direction of commuting distance shocks.

4.2.2. Firm-level controls

We test the robustness of our results by including more firm-level control variables. We manually search all the 1068 firms used in our main analysis in the Compustat data and find financial information for the 405 firms (38%) that have ever gone public, resulting in 9218 matched inventor–firm–year observations. Based on the Compustat data, we obtain firm *Turnover, Market Value*, and *Assets*. From the InfoUSA data, we obtain *Employee Count* and *Sales Volume* at the estab-

[25] We also test for pre-relocation trends in our main regressions by controlling for the pre-relocation trends in our main estimation. Given that these regressions occur at the inventor–firm–year level, we add a dichotomous indicator variable for pre-relocation periods to the main models so that we can control for potential pre-relocation fixed effects in the within-inventor–firm-level analysis. The results remain unchanged with the additional fixed effects.

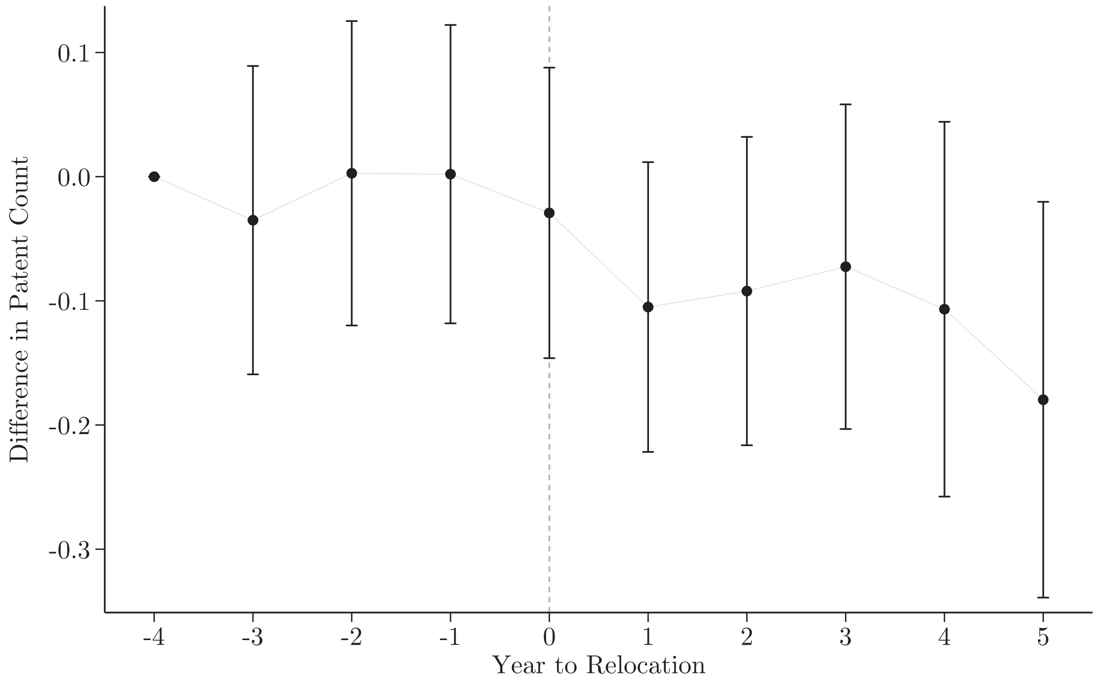

Fig. 5. Effect of Farther Commute Relative to Year of Workplace Relocation Event. Coefficient plot at the inventor–firm–year level. The coefficients are estimated by the fixed-effects OLS regression in Eq. 6. Each dot indicates the difference in the number of granted patents produced by inventors between the inventors having a longer commute due to firm relocations as compared to the other inventors. The dots are plotted against years before and after firm relocations in the horizontal axis.

Table 7
Effect of Commuting on Inventor Productivity—Firm-Level Variables. Fixed-effects OLS regressions at the inventor–firm–year level with subsample observations matched to Compustat. The five self-explanatory firm control variables are added after taking logs. Robust standard errors clustered at the inventor–firm level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.V.:	(1) Patent Count	(2)	(3) Scaled Citation	(4)	(5) Payment Count	(6)
Distance	-0.060**	-0.038	-0.077	-0.036	-0.111	-0.058
	(0.026)	(0.025)	(0.058)	(0.058)	(0.068)	(0.066)
Distance × Top Inventor		-0.262**		-0.467**		-0.600**
		(0.114)		(0.186)		(0.280)
Log Turnover	-0.009	-0.009	-0.007	-0.008	0.017	0.016
	(0.027)	(0.027)	(0.088)	(0.088)	(0.054)	(0.054)
Log Market Value	0.031	0.031	-0.015	-0.016	0.050	0.049
	(0.032)	(0.032)	(0.115)	(0.115)	(0.073)	(0.074)
Log Assets	0.093**	0.094**	0.249*	0.251*	0.149	0.151
	(0.042)	(0.042)	(0.133)	(0.133)	(0.095)	(0.095)
Log Employee Count	-0.012	-0.013	-0.002	-0.002	-0.026	-0.026
	(0.010)	(0.010)	(0.025)	(0.025)	(0.023)	(0.023)
Log Sales Volume	-0.009**	-0.009**	-0.021**	-0.020**	-0.024***	-0.024***
	(0.004)	(0.004)	(0.010)	(0.010)	(0.008)	(0.008)
Mean of D.V. (Pre-Relocation): All Inventors	0.858		1.365		1.816	
Mean of D.V. (Pre-Relocation): Ordinary Inventors		0.781		1.264		1.533
Mean of D.V. (Pre-Relocation): Top Inventors		1.670		2.421		3.276
Inventor–Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Location FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.421	0.422	0.445	0.445	0.408	0.409
Inventor–Firm Count	1493	1493	1493	1493	1493	1493
Observations	9218	9218	9218	9218	9218	9218

lishment level. We log transform these variables because their distributions skew to the right.[26]

Table 7 shows the results of patent quantity and quality regressions in this publicly-traded firm subsample. The estimated coefficients of commuting on inventor productivity are negative and significant, consistent with results from our full sample. Therefore, this result alleviates the concern that there could be some unobserved firm-level variation around relocation events correlated with inventor productivity.

4.2.3. Time-varying amenities

Amenities can play an important role in inventor productivity and determining home location. First, Rauch (1993) finds that local amenities can affect productivity of workers; he treats human capital as a local public good and finds a positive relationship between the

[26] We add 0.01 to the original values so that the zero values are not missing after the log transformation.

Table 8
Effect of Commuting on Inventor Productivity—Time-Varying Amenities. Fixed-effects OLS regressions at the inventor–firm–year level. Instead of Year FE, Inventor Location × Year FE is added to control for time-varying amenity effects around residential locations of inventors. Robust standard errors clustered at the inventor–firm level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.V.:	(1) Patent Count	(2)	(3) Scaled Citation	(4)	(5) Payment Count	(6)
Distance	-0.055**	-0.037*	-0.103*	-0.068	-0.070	-0.037
	(0.022)	(0.021)	(0.058)	(0.057)	(0.052)	(0.051)
Distance × Top Inventor		-0.214***		-0.430**		-0.407**
		(0.082)		(0.175)		(0.175)
Mean of D.V. (Pre-Relocation): All Inventors	0.858		1.365		1.816	
Mean of D.V. (Pre-Relocation): Ordinary Inventors		0.781		1.264		1.533
Mean of D.V. (Pre-Relocation): Top Inventors		1.670		2.421		3.276
Inventor–Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor Location × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.466	0.467	0.431	0.431	0.460	0.460
Inventor–Firm Count	3370	3370	3370	3370	3370	3370
Observations	22,023	22,023	22,023	22,023	22,023	22,023

geographic concentration of human capital and productivity gains. Furthermore, Diamond (2016) shows an endogenous relationship between local amenities and skilled worker home locations, implying that local amenities can affect location decisions of workers. If amenities vary over time, these two channels would bias our results because the current firm location fixed effects may not fully absorb the effects of time-varying amenities.[27]

To ensure that we isolate the effect of commuting distance, we need to rule out the possibility that a differential change in amenities for inventors before and after relocation drives the main result. To account for inventors' residential urban amenities over time, we include residential location-by-year fixed effects, Inventor Location × Year FE, to flexibly control for any neighborhood-level residential amenities as they might change over time. In Table 8, the estimated coefficients are still significantly negative even after controlling for the granular Inventor Location × Year FE, suggesting that time-varying residential amenities do not drive our results.[28]

4.2.4. Additional tests

We also conduct additional robustness tests in Online Appendix A.7. We analyze subsamples for non-Silicon Valley regions, closer and farther relocation groups, single-authored patents, and bounded distance. We also replace the main independent variable, *Distance*, with a categorical variable based on relocation direction and alternative distance measures such as driving distance and drive duration. We also estimate non-linear models, i.e., including the squared term of *Distance* and using conditional Poisson and negative binomial distributions for the dependent variables.

4.3. Sample design and inventor home moving

4.3.1. Intuition

Although our identification strategy seeks to rules out confounding factors in the sample of inventors who did not move their homes, we need to confirm whether our findings for this set of inventors reflectthe broader set of inventors including those not in our sample. For example, if a better-performing inventor is more averse to longer commuting distances, this inventor could move to a different home in response to a firm relocation such that her commuting distance decreases or does not change. In that case, our sample of inventors who did not move their homes (i.e., non-moved inventors) may have a downward performance bias compared to the inventors who moved their residential locations (i.e., moved inventors). To address this consideration for the design of the sample, as a first-order test, we investigate whether there is any pre-firm-relocation performance difference between the moved and non-moved inventors. This section explores the performance trends of these two groups of inventors prior to a firm relocation.[29]

4.3.2. Empirical analysis

We conduct a descriptive analysis that plots pre-firm-relocation performance trends of inventors who changed their home locations after firm relocations (i.e., moved inventors, $n = 2,913$) and those who did not (i.e., non-moved inventors, $n = 3,417$). Fig. 6 presents binned scatter plots depicting the average inventor performance of these two inventor groups for the five years prior to their respective firm relocating. As performance measures, we use the three main patent-based measures of innovation quantity and quality, i.e., *Patent Count, Scaled Citation*, and *Payment Count*. The unit of observation is an inventor–year dyad. Given that we want to explore the patterns of a possible trend while minimizing any limiting assumptions or restrictions, we exclude most of the controls and fixed effects used in the main analyses, and we only include year fixed effects in the generation of the binned scatter plot.

Across all three measures, we do not find any observable differences between the moved and the non-moved inventors in their pre-firm-relocation performance trends. In addition, we note that the trends appear nearly flat for both categories of inventors: this reaffirms the expectation that the samples are well-balanced. In addition to this descriptive analysis, we conduct a more comprehensive regression analysis

[27] We also investigate the role of time-varying amenities at workplaces, based on the same lines of reasoning; amenities at workplaces can affect productivity of workers, and firms may consider this effect in their (re)location decisions. We conduct similar tests for the workplace-level amenities by including modified time-varying fixed effects at firm locations. The results of these tests remain consistent with the main results.

[28] We also consider additional fixed effects for residential amenities: difference in amenity effects before and after relocation (i.e., Inventor × Location FE) and time-varying amenity effects (i.e., Inventor × Year FE). These fixed effects do not change the main results.

[29] Even if there is no pre-firm-relocation performance difference between the moved and non-moved inventors, it is possible for them to have different sensitivity to distance *after* a firm relocation. That is, the moved inventors could be more sensitive to (and affected more by) longer commuting distance although they were not necessarily better-performing than the non-moved inventors before firm relocations. Because our available data cannot completely rule out this possibility, we recommend a conservative interpretation of the main estimates as a lower bound of true distance effects on innovation performance. That said, we suspect that a potential difference in sensitivity would be limited since there is no observable performance difference between the groups. Online Appendix A.6.2 conducts additional tests with an extended data sample to rule out this potential difference in sensitivity.

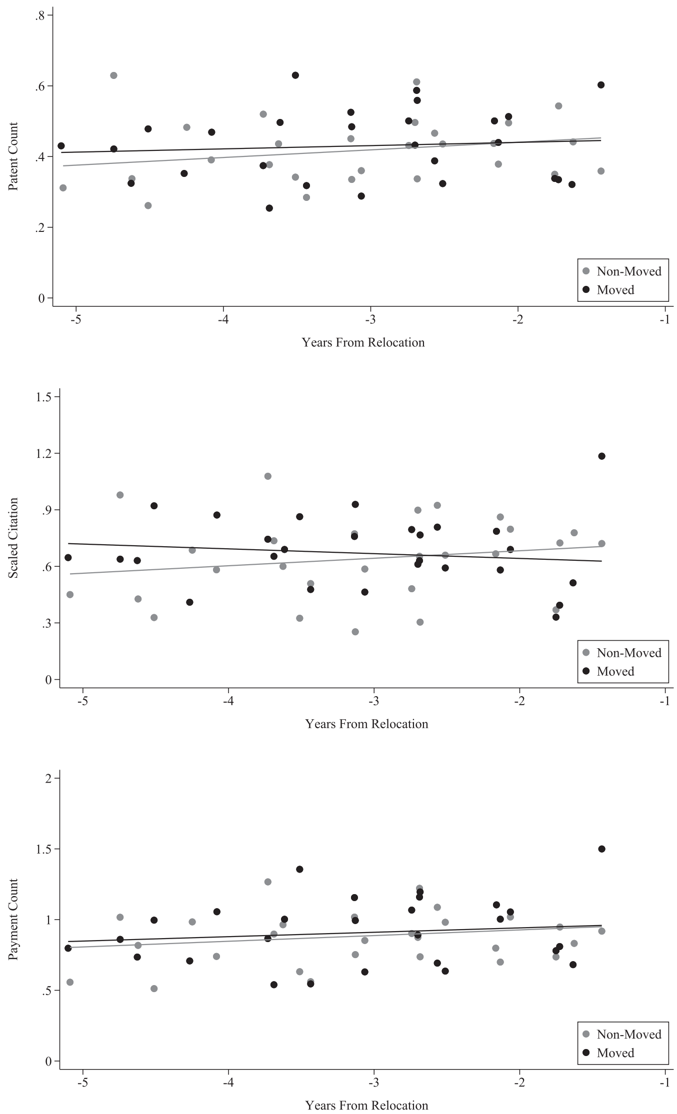

Fig. 6. Innovation Performance before Firm Relocations—Moved and Non-Moved Inventors. Binned scatter plots at the inventor–year level. The dark dots represent the inventors who moved their home locations (i.e., Moved), and the gray dots indicate the inventors who did not move their home locations (i.e., Non-Moved). *Patent Count* is the number patents granted to an inventor per year before firm relocations. *Scaled Citation* re-scales the total number of forward citations to patents received by an inventor per year before relocations, and *Payment Count* calculates the number of maintenance fee payments made by a firm per inventor–year before relocations.

that validates the consistency of pre-firm-relocation performance trends between the moved and non-moved inventors.[30] We find no statistically significant evidence for a difference in pre-firm-relocation performance trends between these two groups of inventors.

We step back to reflect on why we do not observe a difference in pre-firm-relocation performance trends between the moved and non-moved inventors. We believe a key plausible explanation is the existence of salient costs for inventors to move homes. Although the intuition that better-performing inventors have a greater incentive to change their home locations to avoid longer commutes makes sense *ex ante*, home moving costs may make that decision less clear for an individual inventor. Furthermore, it is also plausible that at least some better-performing inventors may also have higher implicit moving costs because the opportunity cost of the time and effort needed for home moving would be more expensive for them.

5. Conclusion

Commuting is costly for employees. In 2014, 139 million U.S. workers made daily commutes to work, averaging 26 minutes each way (Ingraham, 2016).[31] The total opportunity cost of commuting for workers can exceed their hourly wages (Van Ommeren and Fosgerau, 2009), amounting to thousands of dollars per average worker per year (Perino, 2019), and this is before taking into account potential costs on workers' subjective well-being (Kahneman and Krueger, 2006). But how costly is commuting for inventors—an especially important type of skilled worker—in terms of lost productivity?

We empirically investigate how commuting distance affects the productivity of inventors. To test this, we use firm relocation as an exogenous variation of commuting distance and design a difference-in-differences model based on the relocation event. This empirical strategy identifies the causal effect of commuting distance on productivity, separated from confounding sorting effects by both firms and inventors. We find evidence that commuting negatively affects inventor productivity, with every 10 km increase in commuting distance leading to about a 5% decrease in patenting quantity and a 7% decrease in patenting quality. The negative effects are stronger for top inventors whose productivity is within the top 10% among all inventors.

5.1. Implications for managers and policymakers

Our results provide important implications for managers and firms in knowledge-intensive industries. Firms should encourage their inventors to live closer to their workplaces and consider commuting distance when making office location decisions, with greater consideration for their highest-performing inventors. Some major technology firms already incentivize their employees to live closer to the workplace. In 2015, Facebook offered employees working at its Silicon Valley headquarters over $10,000 to move closer to the office and avoid the lengthy and time-consuming commute from San Francisco to Menlo Park, CA (Reuters, 2015). Other technology businesses, like Google, are building proximate housing for their employees.

For policymakers, our findings support the importance of density in urban planning policy. Although it is *ex ante* clear that inventors themselves incur a time and monetary cost from commuting, we show that commuting imposes a further indirect cost on inventor productivity, borne by both the inventor and her employer. Thus, increasing zoning and other land-use restrictions on multifamily construction have an unintended efficiency cost, as over the last few decades these policies increased the average commuting time across the United States (Gyourko et al., 2008, 2019).

5.2. Telecommuting: COVID-19 and future of work

The COVID-19 pandemic of 2020 caused a dramatic change in work environments and forced firms and skilled workers into telecommuting and remote work arrangements heavily reliant on videoconferencing and other virtual collaboration tools. Although some of this shift away from in-office work might be transitory, recent events suggest that the shock of the pandemic may have a permanent shock on some or many organizations. For example, technology firm Twitter announced in May 2020 that its workers can choose to permanently stay remote and not return to the physical office (e.g., Dwoskin, 2020). In light of these recent trends in remote work, it is crucial to consider our findings on the effect of physical commuting on innovation in the context of telecommuting.

[30] See Online Appendix A.6.1.

[31] Assumes fifty work weeks in a year, with five work days per week and a round-trip commute each day.

As the most direct implication of our finding that physical commuting has a negative on the performance of inventors, telecommuting could attenuate that cost by substituting for physical commuting, suggesting that firms should seriously consider allowing for more telecommuting, at least among more distant employees.

Going beyond that immediate implication, an interpretation of our findings in the context of existing literature on telecommuting and remote work suggests a greater degree of complexity in understanding the relationships between physical commuting, telecommuting, and innovation performance. While a full analysis would be beyond the scope of the present study, we hope to provide some intuition here that can guide future research on this essential matter. Consider two scenarios for which telecommuting changes work environments: a hybrid work environment where skilled employees commute to a physical office and telecommute to work remotely, and a pure remote work environment without any commutes to the office. In the hybrid work scenario, recent work by Choudhury (2020) and Choudhury et al. (2020) suggests that provisioning of telework—often framed as a "work-from-home" or even "work-from-anywhere" policy—could prompt workers to move further from the office than we would traditionally expect. Thus, the hybrid environment could increase commuting distance, and our research implies that this pattern may result in poorer innovation performance for in-office work requiring physical commuting. However, our findings on the effect of physical commuting do not provide insight towards the innovation that comes about during remote work.

In the second scenario, a pure remote work environment assumes no physical commuting at all. Although there is no existing literature looking directly at the relationship between telecommuting and innovation, we can triangulate some key mechanisms on two dimensions. The economics and management literatures conceptualize innovation as a combination of *general productivity* (i.e., value, usefulness) and *creativity* (i.e., novelty) (e.g., Amabile, 1983; Bloom and Van Reenen, 2010; Ghosh and Wu, 2020; Nelson and Winter, 1982).

To decompose the effect of telecommuting on innovation, we need to consider its effects on general productivity and creativity, both of which are necessary for innovation. Importantly, telecommuting may have opposing effects on these dimensions of performance underlying innovation. On the one hand, telecommuting could improve general productivity through increased time availability and improved work efficiency per unit of time (Bloom et al., 2015; 2011). Although prior studies focus on relatively less-skilled employees than inventors (e.g., call center employees), telecommuting could plausibly have a positive effect on the general productivity of inventors. For instance, Bartik et al. (2020) find that the COVID-19 pandemic facilitated a more rapid transition to remote work in skilled knowledge work relative to other types of work. On the other hand, telecommuting can negatively affect important antecedents to creativity, limiting interpersonal communication and collaboration. A recent study by Microsoft finds that work-from-home policies during the COVID-19 pandemic reduced the time for collaboration (Yang et al., 2020). In addition, early studies of virtual work find that it limits improvisational and experimental teamwork (Gibson and Gibbs, 2006) and learning from others (Cooper and Kurland, 2002). Taking these two opposing consequences of telecommuting at face value, it remains unclear what effect telecommuting would have on innovation performance.

5.3. Future research

There are several avenues for future research. First, future studies could unpack the relationship between commuting distance, inventor wages, and inventor productivity. Wages are an important channel in the endogenous relationship between commuting distance and productivity (Brueckner, 2001), especially given that an efficiency wage can affect productivity (Ross and Zenou, 2008). Our research could not leverage detailed wage data for inventors due to the highly confidential nature of the tax data sources. Given the lack of wage data, we interpret the results by conceptualizing the potential role of an efficiency wage, without directly investigating this channel empirically. It would be worth investigating the wage dynamics of inventors in regard to changes in commuting distance to identify the potential role played by efficiency wages versus the "pure" effect of commuting on productivity.

Second, the literature shows that amenities can affect productivity of workers (Rauch, 1993) and that workers choose their locations partly based on local amenities (Diamond, 2016). Given that inventors are more likely to be knowledge-sensitive, and concentrating high-skilled inventors can strengthen spillover effects, studying the role of amenities in innovation performance would be an interesting research question. For purposes of the present study, we control for the potential amenity effects—with time-varying amenity fixed effects in our robustness checks—rather than directly investigating how amenities affect inventors. With detailed data on local amenities, one could delve into how (changes in) amenities influence innovation outcomes.

Third, further work should explore the exact mechanisms underlying our identified negative elasticity between commuting and inventor productivity. Although we offer suggestive evidence that commuting disproportionately affects inventor productivity for the top inventors, several potential mechanisms could be at work. For example, inventors with a longer commute could spend less time at work, or they could be less productive at work, etc. More detailed time-use data at the inventor level would allow for future research to disentangle these factors. In particular, clarifying the underlying mechanisms with detailed data could also separate out the effects of physical commuting on general productivity and creativity; as previously alluded in Section 5.2, this granularity would also provide intuition for understanding telecommuting (Kun et al., 2020).

Finally, there needs to be more research to empirically identify the effect of commuting distance on productivity for other types of skilled workers. Human capital underlies the technological innovation that is critical for the performance of firms in high-technology industries (Clough et al., 2019; Hall et al., 2005). More importantly, closer commuting distance could be more critical for skilled workers because it can free up time for in-person communication and collaboration (Battiston et al., 2020) and thereby facilitate knowledge sharing and spillovers between workers co-located at a workplace. Prior studies highlight this channel as a crucial factor in generating innovation (Jaffe et al., 1993; Catalini, 2017). Consequently, future work could expand on generalizing our particular findings on the link between distance and patenting to other knowledge-intensive industries.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jue.2020.103300.

CRediT authorship contribution statement

Hongyu Xiao: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Supervision, Funding acquisition. **Andy Wu:** Conceptualization, Methodology, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Jaeho Kim:** Software, Validation, Investigation, Data curation, Writing - review & editing, Visualization.

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