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Compensating differentials in experimental labor markets☆

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ABSTRACT

The theory of compensating differentials has proven difficult to test with observational data: the consequences of selection, unobserved firm and worker characteristics, and the broader macroeconomic environment complicate most analyses. Instead, we construct experimental, real-effort labor markets and offer an evaluation of the theory in a controlled setting. We study both the wage differentials that evolve between firms with varying degrees of disamenity and how these differentials are affected by worker mobility and therefore selection. Consistent with the theory, we find that riskier firms must pay significantly higher wages to attract workers. Further, when workers are mobile, they sort into firms according to their attitudes towards risk and, as a result, the compensating differential shrinks. Last, we are also able to mimic the biases associated with observational studies.

The whole of the advantages and disadvantages of the different employments of labour and stock must, in the same neighborhood, be either perfectly equal or continually tending to equality. (Smith, 1976 [1776], Book I, ch. X, p. 111)

1. Introduction

Almost two and a half centuries after Smith (1976) first described the basic logic behind compensating differentials, perhaps "*the* fundamental (long-run) market equilibrium construct in labor economics" (Rosen, 1986), considerable doubt remains about the size, and sometimes even the existence, of differentials for even the most salient of disamenities, including death.[1] In principle, calculation of an equalizing difference, the compensation needed to make the marginal worker indifferent between positions with and without disamenities, should be straightforward. In practice, however, credible estimates have proven elusive, for at least two sets of reasons.

The first reason reflects the limitations of observational datasets. Data at both the firm- and job-level is often scarce, which means that important distinctions are either unobserved or measured at inappropriate levels of aggregation. It is often the case, for example, that disamenities are measured at the sectoral, and not firm, level, which can cause researchers to overestimate differentials (Dorman and Hagstrom, 1998). More often than not, researchers also lack sufficient individual-level data to control for firm- and sector-level selection, which makes it difficult to evaluate competing explanations of small wage differentials, including "market failure" or efficient selection (Goddeeris, 1988; Garen, 1988; Kostiuk, 1990; Hwang et al., 1992; Lavetti, 2014).

The second set of challenges is rooted in various labor market complications, and would muddle estimation even with more complete datasets. For example, the standard rationale for the emergence of compensating differentials presumes vigorous and well-informed job search in a world where labor market frictions and incomplete information are absent (Hwang et al., 1998; Bonhomme and Jolivet, 2009). Without evidence on motivation, it can also be difficult to distinguish between voluntary and involuntary job changes (Taber and Vejlin, 2011). Furthermore, if work at firms with disamenities is also harder to observe, or write contracts on,

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[1] For example, Kniesner et al. (2012) use panel data to report estimates of the value of a statistical life between $6 and $26 million, in which the confidence interval for the former includes zero. Worse, perhaps, Dorman and Hagstrom (1998) find that, for non-union workers, the mean differential is in fact negative.

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2214-8043/

wage differentials will also include a rent (Ho, 2013). Macroeconomic conditions – in particular, the jobless rate – can also influence firm-level differentials (Dorman, 1998).

Despite these challenges, labor economists have attempted to measure, and evaluate, compensating differentials in the field. There are many papers on compensation for health risks, from the existence of a wage premium for oil workers at sea and on the permafrost, to military bonuses for combat troops, or even higher rates for sex workers who do not insist on condom use (Rao et al., 2003). There are likewise numerous studies of income risk, the disamenity that we study in this paper. In some cases, this risk assumes the form of a small likelihood of a large payoff, as in the arts, sports or entertainment (Hartog and Vijverberg, 2007). In other cases, the income risk comes from an increased likelihood of job loss, including the chance that accidents can lead to long unemployment spells (Hamermesh and Wolfe, 1990). Citing concerns similar to those discussed above, Mas and Pallais (2016) focus on workers' preferences, rather than on the emerging differential. In a recent large scale field experiment, they measure workers' willingness to pay for flexible or predictable work hours and the ability to work from home by asking job applications to make a binary choice between two alternate work arrangements with different wages.

Our paper makes two substantial contributions to the literature. First and foremost, we are, to our knowledge, the first to use experimental labor markets to construct "clean" estimates of compensating differentials in the face of well-defined risks, both with and without worker sorting. Second, because our data also allow us to mimic what a researcher with incomplete observational data would see, we can reproduce, but also better understand, the biases embodied in conventional estimates, a novel application of experimental methods. We believe that this exercise illustrates an important but under-appreciated application of economic experiments.

The challenges faced by researchers measuring differentials using observational data suggest the usefulness of using a controlled laboratory experiment to contribute a clean test of the theory. The lab provides three main advantages. First, we can ensure that jobs differ only in a well-defined disamenity that we induce. We construct experimental labor markets that allow us to control the basic determinants of wages – the production process, output prices, labor demand – as we introduce cross-firm variation in the riskiness of compensation. The disamenity in our design is consistent with the presence of either income and/or employment risk, an example that Smith (1976) discussed at length, and which we choose due to its canonical stature in the literature. Since there are no other differences in the managerial decision problem, any wage differentials that arise should reflect the firms' response to the revealed preferences of workers for the disamenity. Second, because the "workers" are experimental participants, we are able to elicit measures of each worker's risk preferences in order to assess their tolerance for the disamenity. Finally, our experimental design allows us to vary worker mobility so that we can cleanly assess the effect of worker sorting on the differential.

Our design, with its emphasis on the effects of commuting costs on compensating differentials, is unique.[2] Firm managers compete on piece rates to attract workers to their firms, where they exert real effort. The firms are identical, except that in one firm we introduce a disamenity: in each period, there is a 25% chance that a worker's effort, and thus earnings, will be lost. To measure worker tolerance for the disamenity, we collect incentivized risk attitudes from all of our participants.

To evaluate the effects of selection, we include two mobility treatments. Workers are randomly assigned to the catchment area of one of the two firms, but can commute to the other firm at a cost. By varying the commuting cost, we control the extent to which endogenous sorting can occur, and thus can measure the effect of sorting on the differential. In one treatment, it is costly for workers to commute from one firm to another, and, as expected, relatively few do. Since workers also have a self-employment option, the resulting wage difference in this treatment can be understood as the "full" or "pre-sorting" differential. In the second, high mobility, treatment, it is much cheaper for workers to migrate, which allows us to evaluate how much the matching of workers and firms reduces the full differential – a result with important theoretical and empirical implications.

The design allows us to avoid the two main challenges described above. First, we can study the evolution of compensating differentials in the absence of competing labor market complications; and, second, we can directly observe both firm characteristics (which we control) and worker characteristics (which we measure).

In this setting, we find considerable support for the Smithian model of compensating differentials. In almost all sessions, a significant differential, in both substantive and statistical senses, soon emerges and persists. Unless the marginal worker is risk-loving, however, the differential isn't sufficient to compensate workers for their assignment to the risky firm. In this sense, even in our "stripped down" environment, markets fail. We further find that the differential does shrink when workers are mobile and, consistent with the basic theoretical model, that workers sort on the basis of their risk preferences. We find that the effect of selection, or worker-firm matching, is equivalent to between one quarter and one third of the full differential.

Last, to link our work to previous studies that examine naturally occurring data, we show that a researcher who had access to all of our data except for worker characteristics, a common deficit, would underestimate the differential almost 25%, while a researcher forced to use sectoral, rather than firm, characteristics would vastly overestimate it. We view our results as both a robustness check and confirmation of longstanding concerns about potential biases in conventional studies.

The paper proceeds as follows. Section 2 provides a conceptual framework and describes the experimental design and measurement of worker tolerance for the disamenity. Section 3 reports our results and is organized around the three main questions our experiment was designed to address: (1) Do differentials arise to compensate workers for a risky disamenity? (2) Do workers sort according to their tolerance for the disamenity? and (3) Do differentials shrink when mobile workers are able to sort according to their preferences? As hinted at above, Section 4 concludes with a discussion of how our experimental data – which includes complete information on worker preferences, commuting costs, and job-level disamenity – can be used, not only to address these questions, but to assess how the measurement of our differentials would be affected if we had access to less complete information on worker or job characteristics.

2. Experimental design

2.1. Conceptual framework

The intuition for our predictions is rooted in Rosen's (1986) canonical treatment: labor markets produce better matches between firms and workers when the latter are mobile. If it is easier, for example, for firms with uncertain compensation schemes

[2] The closest experiments to ours are Fehr et al. (1996a, 1996b) in that these authors are also interested in wage setting dynamics, but the focus of these papers (on gift exchange and the evolution of non-compensating differentials) is very different.

to find risk tolerant workers, the compensating differential should fall. To formalize this, and to introduce some additional considerations, we construct the simplest possible model that embodies the essential features of our experimental design.

Suppose there are two towns, each with a single risk neutral firm and a continuum of workers. Suppose, too, that the risk preferences of individual workers can be expressed $U_i = \overline{W} - \frac{1}{2} r_i \sigma_W^2$, where $\overline{W}$ is expected wage income, σ_W^2 is its variance, and r_i is the coefficient of absolute risk aversion, a specification sometimes rationalized as a second order approximation to more general preferences. Let the distribution of the risk aversion parameter in each town be denoted $F(\cdot)$.

Assume that in one of the towns, a safe firm, called the S-firm, offers workers a fixed wage $\overline{W}^S$, while in the other, a risky firm, the R-firm, offers $\overline{W}^R$ in expectation, with variance σ_R^2. Consistent with our protocol, we also assume that workers in both towns have an alternative, "home production," that provides a fixed wage $\overline{W}$. Each worker hired expends one normalized unit of effort and produces one normalized unit of output that the firm sells for price P, which implies that firm j's expected profits per worker are equal to $P - \overline{W}^j$.

We consider two extreme cases, one in which commuting between the two towns is frictionless and another in which the costs are so high that workers would not commute.[3] In the high cost case, the S-firm maximizes its profits when it offers a wage equal to that available in home production, or $\overline{W}^S = \overline{W}$. To understand the R-firm's choice, we observe that when it offers $\overline{W}^R$ in expectation, all of the workers in the same town for whom $\overline{W}^R - \frac{1}{2} r_i \sigma_R^2 \geq \overline{W}$ or, in other words, $r_i \leq \frac{2(\overline{W}^R - \overline{W})}{\sigma_R^2}$ will accept. The R-firm's scaled labor force is therefore $F(\frac{2(\overline{W}^R - \overline{W})}{\sigma_R^2})$, which depends, as one would expect, positively on the expected wage differential and negatively on the variance or size of the relevant disamenity. The R-firm's scaled expected profits are therefore $(P - \overline{W}^R) F(\frac{2(\overline{W}^R - \overline{W})}{\sigma_R^2})$, which are maximized when:

$$(P - \overline{W}^R) f\left(\frac{2(\overline{W}^R - \overline{W})}{\sigma_R^2}\right) \frac{2}{\sigma_R^2} - F\left(\frac{2(\overline{W}^R - \overline{W})}{\sigma_R^2}\right) = 0$$

or:

$$P = \overline{W}^R + \frac{\sigma_R^2}{2} \frac{1}{IMR(\frac{2(\overline{W}^R - \overline{W})}{\sigma_R^2})}$$

where $f(\cdot) = F'(\cdot)$ is the population density of risk aversion and $IMR(\cdot) = f(\cdot)/F(\cdot)$ is the inverse Mills ratio.

To explore the implications of this condition, consider the simplest possible example, in which the distribution of the risk aversion parameter is uniform between 0 (that is, risk neutral) and some $r_{\max}$. In this case, the value of the inverse Mills ratio, evaluated at the relevant point, is $\frac{\sigma_R^2}{2(\overline{W}^R - \overline{W})}$ and, after simplification, the optimal choice of $\overline{W}^R = (1/2)(P + \overline{W})$, which generates a compensating differential $\overline{W}^R - \overline{W}^S$ equal, in expectation, to:

$$\overline{W}^R - \overline{W}^S = \overline{W}^R - \overline{W} = \frac{1}{2}(P - \overline{W}) > 0$$

In this environment, there is a positive differential, and it is proportional to the difference between the price (or, in more general terms, the marginal revenue product of labor) and the value of home production to the worker. It does *not* depend, however, on the variance of the R-firm's wage contract. We further note that there is no reason, even in the low cost case, to suppose that the firms will attract equal numbers of workers. In particular, the threshold level of risk aversion in this case is $\frac{2(\overline{W}^R - \overline{W})}{\sigma_R^2}$ or, substituting the relevant equilibrium values, $\frac{(P - \overline{W})}{\sigma_R^2}$. The R-firm will therefore hire more workers when compensation variance is low, when the price of output or demand is high, or when the value of home production is low.

How does this differential change when commuting costs are reduced, and the two firms together confront what amounts to a consolidated "two town labor market"? We first note that the S-firm will need to post a wage $\overline{W}^S$ that is greater than or equal to $\overline{W}$, which means that from the perspective of the R-firm, workers will now compare the bundles $(\overline{W}^R, \sigma_R^2)$ and $(\overline{W}^S, 0)$. It follows that when $\overline{W}^R$ is offered to workers from both towns, $2F(\frac{2(\overline{W}^R - \overline{W}^S)}{\sigma_R^2})$ will accept, generating profits of $2(P - \overline{W}^R)F(\frac{2(\overline{W}^R - \overline{W}^S)}{\sigma_R^2})$. The first order condition resembles the monopsonist's condition derived earlier but now embodies an implicit reaction function:

$$P = \overline{W}^R + \frac{\sigma_R^2}{2} \frac{1}{IMR\left(\frac{2(\overline{W}^R - \overline{W}^S)}{\sigma_R^2}\right)}$$

In contrast, the S-firm will attract $2(1 - F(\frac{2(\overline{W}^R - \overline{W}^S)}{\sigma_R^2}))$ workers – that is, all the risk averse workers from both towns for whom $r_i \geq \frac{2(\overline{W}^R - \overline{W}^S)}{\sigma_R^2}$ – and maximize expected profits $2(P - \overline{W}^S)(1 - F(\frac{2(\overline{W}^R - \overline{W}^S)}{\sigma_R^2}))$. Its reaction function is implicit in the first order condition:

$$P = \overline{W}^S + \frac{\sigma_R^2}{2} \frac{1}{H\left(\frac{2(\overline{W}^R - \overline{W}^S)}{\sigma_R^2}\right)}$$

where $H(\cdot) = f(\cdot)/(1 - F(\cdot))$ is the hazard function for the risk aversion parameter.

To illustrate some of the properties of the implied equilibrium, consider, once more, the case where the distribution is uniform $[0, r_{\max}]$ in both towns. Building on an earlier result, the R-firm's reaction function is $\overline{W}^R = (1/2)(P + \overline{W}^S)$. Following similar logic, the S-firm's reaction function is $\overline{W}^S = (1/2)(P + \overline{W}^R - (1/2) r_{\max}\sigma^2)$. It is worth noting, that as the "safe haven," the S-firm can offer lower wages when R-firm work is associated with higher risk. It can also reduce its wages as the population becomes more risk averse, that is, $r_{\max}$ rises. It is then not difficult to show that the Bertrand equilibrium wage offers are:

$$\overline{W}^R = P - \frac{r_{max}\sigma^2}{6} \quad \text{and} \quad \overline{W}^S = P - \frac{r_{max}\sigma^2}{3}$$

with compensating differential equal to:

$$\overline{W}^R - \overline{W}^S = \frac{r_{max}\sigma^2}{6}$$

(The existence of a non-degenerate equilibrium requires that the S-firm wage $\overline{W}^S$ exceed the value of the outside option $\overline{W}$ or, substituting from above and then rearranging, that $P - \overline{W} > \frac{r_{\max}\sigma^2}{3}$, which we assume here.)

The comparative statics for both the absolute offers and the differential with respect to "market shocks" are more or less intuitive: an increase in the price of output P or, in more general terms, a

[3] We note that the model becomes intractable when commuting costs are included as a general parameter, rather than focusing on the extreme cases in which costs are assumed to be close to zero or insuperable, without changing its basic properties. For purposes of exposition, then, our motivating parable removes this complication.

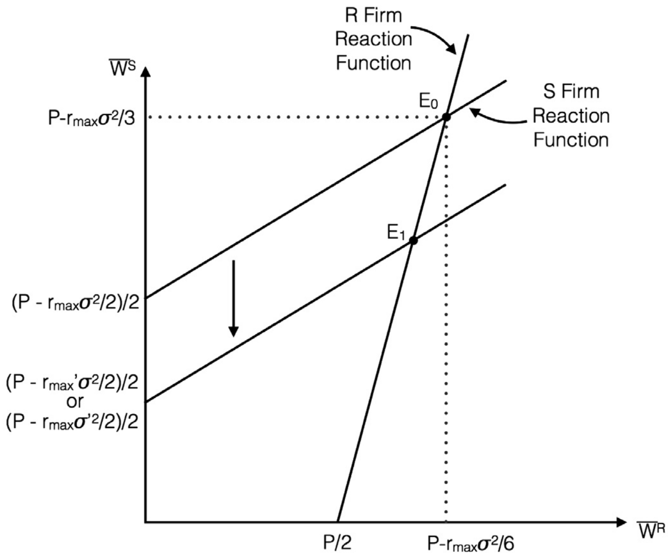

Fig. 1. Best response functions of S(afe) and R(isky) firms when commuting costs are low, $r'_{max}\sigma^2 > r_{max}\sigma^2$ or $r_{max}\sigma'^2 > r_{max}\sigma^2$.

positive demand shock causes wages at both firms to rise without, in this case, a change in the compensating differential. To understand the effects of either a more risk averse population or increased risk at the R-firm, consider Fig. 1, in which we plot the reaction functions for both S- and R-firms. An increase in either r_{max} or σ^2 does not cause the R-firm reaction function to shift, but does cause the S-firm reaction function to shift downward: for reasons mentioned earlier, the S-firm can now afford to reduce its wage offer $\overline{W}^S$, given $\overline{W}^R$. As Fig. 1 suggests, however, this drives the equilibrium wages at *both* firms downward: as the S-firm reduces the value of its offer, the R-firm will follow suit, and so on. It also implies, however, that as we move along the R-firm reaction function, the R-firm wage $\overline{W}^R$ will fall less than the S firm wage $\overline{W}^S$ which means that the compensating differential $W^R - W^S$ will rise.

This motivating model rationalizes our two most important predictions. First, as the costs of migration between towns fall, and the matches between firms and workers improve, the compensating differential decreases, from $(1/2)(P - \overline{W})$ to $\frac{r_{max}\sigma^2}{6}$. (From above, we know that the differential decreases because equilibrium existence requires that $P - \overline{W} > \frac{r_{max}\sigma^2}{3}$.) Second, as these costs fall, there is selection on r, the coefficient of absolute risk aversion.

2.2. Experimental labor market set-up

Participants were recruited from the undergraduate student body at Middlebury College. The students were assigned to “labor markets” of six participants each. Within each labor market, there were two firms: the Safe (Red) Firm and the Risky (Blue) Firm.[4] Two of the six participants were assigned to be managers and the remaining four participants were workers. Each manager was tied to a single firm but workers could move between firms. These roles were fixed for the duration of the experiment, which lasted 15 periods. Participants interacted using the experimental software z-Tree (Fischbacher, 2007).

The manager’s job was to set the piece rate in his firm and he could choose any integer between 1 and 100 experimental points. To simplify the tâtonnement process of wage setting, the managers made this choice sequentially at the start of every period. In each period, it was randomly determined whether the Safe Firm manager or the Risky Firm manager went first. The workers then viewed the piece rates at both firms and chose which firm to join for the period. Workers could always choose to switch to a different firm in the following period. Workers also had an outside option: rather than choosing to work at one of the two firms they could choose the “Orange Option,” self-employment, which paid a piece rate of 40 points. This set a floor, below which wages should not fall.

The workers then completed a real effort task. They had one minute to solve addition problems and their earnings were determined by their output and the piece rate either set by the manager of their firm or the one linked to self-employment. Solving addition problems is a common task in the related literature (e.g., Sutter and Weck-Hannemann, 2003 or Niederle et al., 2013) and our workers could produce as many sums from three two-digit numbers as possible during the minute. For each unit of output produced by a worker in his firm, the manager earned 100 points minus the piece rate.[5]

To incentivize participants to treat each period separately (Hey and Lee, 2005), they were paid according to their earnings from one randomly selected period plus their earnings from one randomly chosen decision from a risk preference elicitation task described below. These earnings were converted to US dollars at the rate of 25 points = 1 USD and added to a $5 show-up fee.

2.3. Differences between firms and mobility

In the Safe Firm, workers’ earnings for the period were equal to the piece rate times the number of problems correctly solved. In the Risky Firm, however, this was true only with probability 0.75. With probability 0.25, the worker’s output would be lost and he would not be paid for the period’s work. Each period, this was determined by a different random draw for each worker in the Risky Firm. The risk that the workers in the Risky Firm faced was common knowledge among all participants. The manager of the Risky Firm was always paid according to the worker’s output, even if the worker was not, so that the Risky Firm manager faced no additional risk. All else equal, we expected that the resulting disamenity would cause all workers to prefer the Safe Firm, providing the conditions for a standard compensating differential to evolve to compensate Risky Firm workers for their expected loss.

To address the question of whether selection leads to smaller compensating differentials, we varied the mobility of the workers by introducing commuting costs. Specifically, the participants were told that two of the four workers in the labor market lived near the Safe Firm and two lived near the Risky Firm. In order to work at a firm outside one’s home zone, the worker must pay a fixed commuting cost for that period. There was no cost associated with working at the firm within one’s home zone or with choosing self-employment. We conducted two treatments: one with a low commuting cost of 10 points per period (*Low Cost*) and one with a much larger commuting cost of 100 points per period (*High Cost*).[6] The commuting cost was subtracted from the worker’s earnings for the period. A worker who commuted to the Risky Firm and then

[4] In the instructions and throughout the experiment, the Safe Firm was referred to as the “Red Firm” and the Risky Firm as the “Blue Firm” to avoid priming our participants. For the sake of clarity, we use the more descriptive names in the paper. A full set of instructions can be found in the appendix.

[5] We chose to use piece rates instead of a fixed wage to make sure that managers had an incentive to attract workers. Had we used a more simple fixed wage, workers would not have been incentivized to provide effort and, therefore, managers would not have had an incentive to lure workers to their firms.

[6] These parameter values were set after observing participant behavior in a pilot experiment. On average, participants solve between 5 and 6 addition problems each period and they are paid a piece rate greater than 40 (the piece rate of the outside option) for each. Thus paying a commuting cost of 10 has a negligible impact on earnings, while a cost of 100 is substantial.

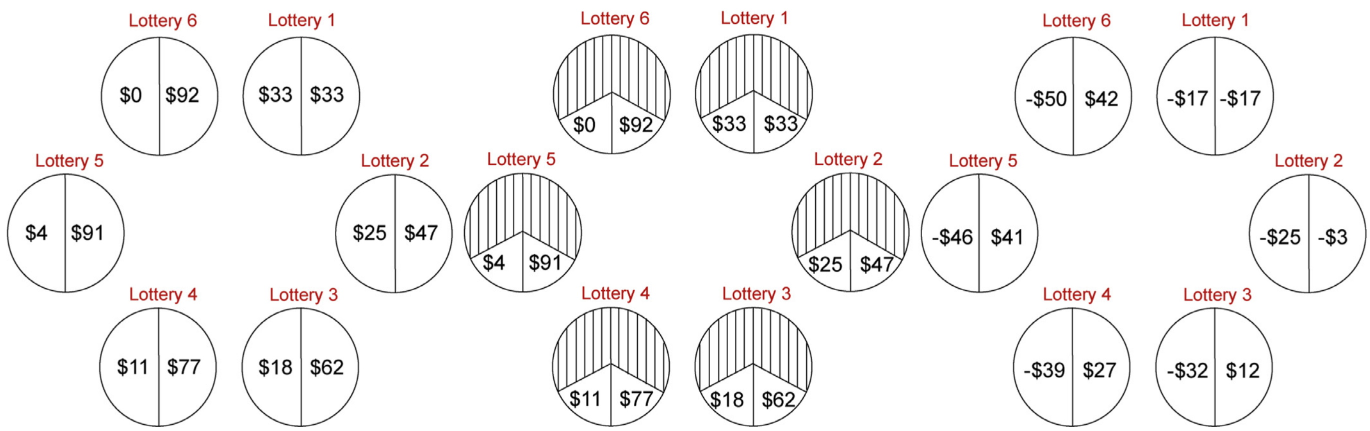

Fig. 2. Three lottery decisions.

lost all earnings for the period would receive a negative payoff, which was subtracted from the show-up fee.

Both the conceptual framework and the details of the design inform our predictions. First, in the High Cost treatment, we expect to see low mobility and significantly higher piece rates at the Risky Firm than the Safe Firm. Consistent with our model, the Safe Firm manager doesn't need to do much better than the outside option of 40 points when commuting costs are so high as to make work outside the home zone difficult, if not impossible. In a similar vein, the Risky Firm manager *would*, however, need to offer a piece rate much higher than 40 for workers to be willing to bear the risk.

Second, we expect that in the Low Cost treatment, workers will sort according to risk preferences and the wage differential should be smaller than in the High Cost treatment. The intuition, as described earlier, is that the most disamenity-averse workers will flock to the Safe Firm. Disamenity-tolerant workers, however, might choose the Risky Firm, and would require a smaller differential to do so.

2.4. Risk tolerance elicitation

Prior to their participation in the main experiment, we elicited participants' tolerance for risk using a survey question about willingness to take risks and three incentivized lottery choices. The survey question asked participants to report whether they are someone who is generally willing to take risks or who avoids risks, measured on a 6-point scale. A similar question is common in large-scale surveys and has been found to be a reliable predictor both of decisions in real-stakes Holt–Laury lottery choices as well as of risky behavior outside the lab, such as smoking, stock market participation, and choosing self-employment (Dohmen et al., 2011).

In addition to the survey question, participants made three lottery choice decisions constructed to elicit their tolerance for risk. In each, participants were presented with six lotteries, as shown in the three panels of Fig. 2, and asked to choose one. At the end of the experiment, so that the outcomes could not affect labor market behavior, one of three decisions was randomly selected and the chosen lottery was implemented. The three decisions are borrowed from a large-scale field study by Carpenter and Cardenas (2013). In addition, this method has also been used in other field studies (e.g., Bogliacino and Gonzalez-Gallo, 2015) and in the lab (e.g., Carpenter et al., 2011).[7]

The first decision, shown in the leftmost panel, was a simple risk preference elicitation. Participants were told to think of each lottery as a bag, containing five high-value balls and five low-value balls. One ball would be drawn from the bag of their choice and they would be paid accordingly. For each decision, the lotteries were numbered clockwise from 1 to 6. Individuals with preferences close to risk neutrality are expected to choose lottery 5, which has the highest expected value (i.e., a coin toss resulting in payoffs of either 4 or 91). Moving from lottery 5 to lottery 6, the expected value decreases as the variance increases, indicating that lottery 6 would be chosen only by risk-seekers. Among the other four lotteries, lower lottery choices indicate greater risk aversion.

The second decision, shown in the middle panel, preserves the same numbers on the high and low value balls in each of the lotteries, but introduces ambiguity in the probability of each being chosen. Rather than knowing that there are five high-value and five low-value balls in each bag, participants are told that there are at least two high-value balls and at least two low-value balls, and that the values of the remaining six balls may be high or low. Following Carpenter and Cardenas (2013) (and implicitly Ellsberg, 1961), we define ambiguity aversion as the difference between the lottery chosen in the left (risky) panel and the lottery chosen in middle (ambiguous) panel: Ambiguity Aversion = Risk Choice Lottery Number - Ambiguity Choice Lottery Number. In other words, someone who chooses a lower, safer lottery number in the presence of ambiguity is said to exhibit positive ambiguity aversion.

In the final decision, shown in rightmost panel, participants are first told that they have been given 50 points to start and that they, again, must pick one of the six lotteries. In this case, the only difference between the leftmost choice and the rightmost choice is framing. The lotteries on the right are identical to those on the left, only the 50 point endowment has been subtracted from each value. Again following Carpenter and Cardenas (2013), loss aversion is defined as the difference between the lottery chosen on the right and the lottery chosen on the left: Loss Aversion = Loss Choice Number - Risk Choice Number. Loss aversion is thus positive if a participant moves to a higher, riskier lottery choice to avoid certain losses.

We chose to collect these two additional risk measures because of their strong predictive power across a variety of behaviors associated with risk. Our measures of ambiguity and loss aversion have been shown to be externally valid and are analogous to other measures used in the literature, which are constructed by comparing decisions with and without ambiguity/loss.[8] For example,

[7] This approach to measuring preferences is similar to the one originating in Ball et al. (2010), which has also been widely adopted in the literature (e.g., Grossman, 2013).

[8] Related instruments include Hogarth and Villeval (2014), which compares the prices submitted for certain and uncertain lotteries, Halevy (2007) and

Table 1
Summary statistics.

	High Cost	Low Cost	Min	Max	t (p)	Z (p)
Survey risk aversion	2.56	2.38	0	5	0.71	0.58
	(1.18)	(1.23)			(.478)	(.56)
Risk choice	2.98	2.91	1	6	0.23	0.12
	(1.64)	(1.45)			(.821)	(.903)
Ambiguity choice	2.94	2.64	1	6	0.82	1.34
	(1.54)	(1.86)			(.413)	(.18)
Loss choice	3.88	3.48	1	6	1.37	1.27
	(1.38)	(1.38)			(.175)	(.203)
Ambiguity aversion	0.04	0.26	−5	5	0.53	1.03
	(2.13)	(1.77)			(.598)	(.305)
Loss aversion	0.9	0.57	−3	4	1.03	1.14
	(1.45)	(1.53)			(.305)	(.256)
Commuting	0.16	0.43			9.45	9.02
	(.367)	(.5)			(.000)	(.000)

Standard deviations in parentheses. The final two columns show *t*-test and Mann-Whitney test statistics with p-values in parentheses.

in Carpenter and Cardenas (2013) associations are found between the loss aversion measure and economic well-being measures such as being a homeowner, and one's levels of relative wealth and monthly expenditures, while the ambiguity aversion measure predicts poverty indices like having basic services (e.g., piped water and trash collection), receiving formal assistance and being self-employed. Similarly, considering the results of Carpenter et al. (2011), because of their association with dopaminergic gene polymorphisms, these measures of ambiguity and loss aversion can be associated with important financial behaviors like holding cash reserves, paying credit card balances and having overdraft protection. Using similar methods, Dimmock et al. (2013) show that ambiguity aversion correlates with stock market participation and diversification in a representative sample from the United States and Chib et al. (2012) find that making incentives stronger works to increase effort up to the point where loss averse workers begin to worry about failure. Considering the broader literature, the evidence suggests that ambiguity aversion is a preference distinct from risk aversion and may be associated with separate personality traits (Borghans et al., 2009). The evidence suggests that it is not closely associated with IQ or cognitive ability and can instead be viewed as a type of pessimism or perceived imprecision in probabilities (Rustichini et al., 2016; Tymula et al., 2012). It is quite possible, then, that ambiguity and loss matter even in environments characterized by "risk" in the narrow sense. Further, to the extent that workers perceive the bad outcome as a loss relative to the prospective income, loss aversion may be especially salient in our environment.

3. Results

3.1. Description of data

We conducted seven labor markets of the Low Cost treatment and eight of the High Cost treatment. Four sessions were conducted, with three or four labor markets running in parallel. Overall, 90 students participated in the experiment. Participants earned \$15.64 on average plus a \$5 show-up fee, with earnings ranging between \$0.16 and \$39. Summary statistics for each treatment are provided in Table 1.

We first look at the risk attitudes elicited with the survey risk question and with the three lottery choices. The first row of Table 1 shows the average level of risk aversion reported by participants in the High Cost and Low Cost treatments, while the next three rows show the average lottery number chosen in each of the three risky decisions. There is substantial variation in the choices made by the participants, with each of the eighteen available lotteries being chosen by at least a few individuals. We find no significant differences across treatments in either the survey risk measure or in any of the three lottery choices. The next two rows show the average Ambiguity Aversion and Loss Aversion in each treatment. Across both treatments, there was considerable variation in both Loss and Ambiguity aversion and, on average, participants exhibited positive Loss Aversion ($p < 0.01$) and positive but insignificant Ambiguity Aversion ($p = 0.49$), both of which are consistent with Carpenter et al. (2011). Again, there is no difference between the two treatments. Additionally, there is no significant difference in the survey risk measure, the three lottery choices, Ambiguity Aversion, or Loss Aversion exhibited by workers assigned to the Safe Firm zone compared with those in the Risky Firm zone (*p*-values all at least 0.31 in both *t*-tests and Mann–Whitney tests). Thus it appears that the random assignment both into treatments and into zones was successful.

One might be concerned that these measures may be associated with the numeracy or cognitive ability of the participants, which could also influence both workers' assessments of piece rate offers and their ability to complete the addition task. We find no correlation between any of our preference measures and the number of addition problems solved by the workers. We further note that, while more productive workers do have more to gain in each work period, a worker's productivity is not necessarily associated with the *piece rate differential* that he or she would require to join the risky firm, which is determined by the worker's risk preferences.

The final row of Table 1 shows the frequency with which workers commute to work outside of their home zones. While workers in the High Cost treatment commute in sixteen percent of opportunities, workers in the Low Cost treatment commute in forty-three percent of opportunities, a difference that is significant at all conventional levels. This indicates that the commuting cost treatments had the intended impact on worker mobility.

3.2. Do differentials evolve to compensate workers for the risky disamenity?

We first look at whether there is evidence of compensating differentials evolving between our two firms. The two panels in Fig. 3 show the piece rates over time in the two treatments. Given this is the dimension on which managers compete and workers make

Borghans et al. (2009), who elicit selling prices for participation in uncertain lotteries, and Tymula et al. (2012), which assess whether the number of safe choices increases in a multiple price list setting as lotteries become uncertain.

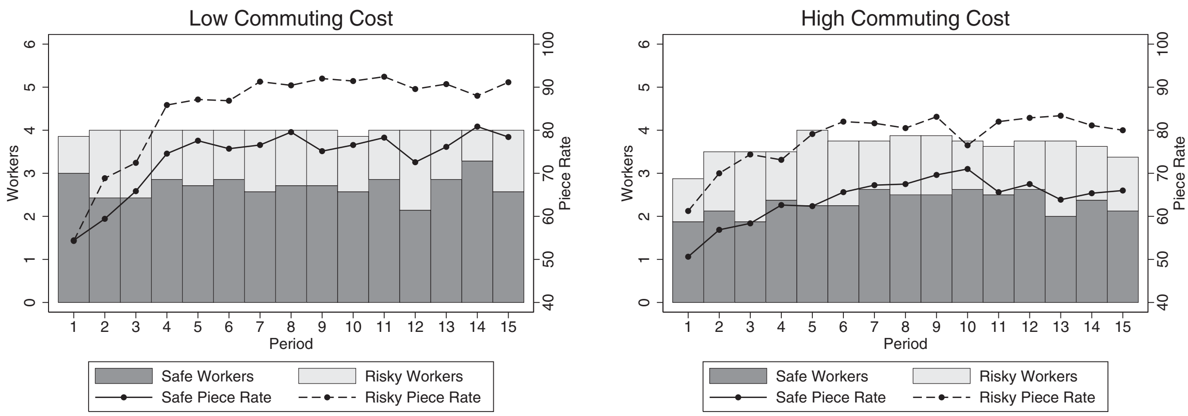

Fig. 3. Piece rates and firm employment over time.

their firm choices, we build our analysis on piece rates. In each panel of Fig. 3, the solid line shows the piece rate in the Safe Firm and the dashed line shows the piece rate in the Risky Firm. In both the High and Low Cost treatments, we observe a stable, significant differential in the piece rates offered between the two firms. The difference between piece rates is significant at all reasonable levels in both treatments.[9] We also note that the piece rates offered by both firms in both treatments are significantly within the interior of the sensible (40, 100) piece rate range and thus the differential is not artificially constrained by the upper or lower piece rate bounds. Our results thus strongly support the prediction that differentials will evolve to compensate workers who are exposed to greater risk. Given our theoretical framework, it is reasonable to wonder whether piece rates set by the Safe Firm in the High Cost treatment reflect the influence of social preferences, since the piece rate exceeds the value of home production. While we cannot rule out this possibility, we also note that there is still competition between firms even when costs are high, as evidenced by the 16% of workers who commute, which would drive wages above the outside option.

Since nearly 90% of the workers in our experiment were either risk neutral or risk averse, one natural benchmark to consider is whether the differential is sufficient to fully compensate workers in expectation for the possibility of losing their earnings in the Risky Firm. To address this question, we test whether 0.75 times the piece rate in the Risky Firm is greater than or equal to the piece rate in the Safe Firm. We can reject this hypothesis in favor of the alternative that the differential is insufficient to compensate risk neutral workers at the $p = 0.04$ level or better for both the High and Low Cost treatments (using one-sided Wilcoxon signed-rank tests). It should be noted, however, that this does not mean that workers choose the "wrong" firm: accounting for commuting costs, the vast majority (approximately 80%) select the firm in which they would receive the highest expected earnings.

The dark gray bars in Fig. 3 show the number of workers in the Safe Firm in the period, while the lighter gray bars show the number of workers in the Risky Firm. In most periods (over 80 percent of observations), the two firms split the workforce, rather than one firm employing all four workers. In the High Cost treatment, workers commute less frequently and the average number of workers in the Safe Firm is not significantly different from two ($Z = 1.48$, $p = 0.14$ in a Wilcoxon signed-rank test taking the labor market as the unit of observation). However, the number of Risky Firm workers is significantly less than 2 ($Z = 2.38$, $p = 0.017$), as a significant number of workers choose the outside option. In the Low Cost treatment, where commuting is more common, we expect workers to forgo the outside option; however, we do not expect the firms to necessarily split the workforce equally in equilibrium. In this case, the Safe Firm attracts 2.7 workers on average, significantly greater than half of the workforce ($Z = 2.37$, $p = 0.018$). From Fig. 3, we also see that the number of Safe and Risky Firm workers typically sum to four when costs are low, indicating that few workers choose the outside option when commuting is inexpensive.

Table 2
Compensating differential by commuting cost.

	(1)	(2)
Low Cost treatment	−0.312***	−0.317***
	(0.089)	(0.086)
Risky manager first		−0.056**
		(0.021)
Constant	0.678***	0.736***
	(0.223)	(0.217)
Manager controls	Yes	Yes
Worker controls	Yes	Yes
Observations	225	225
Clusters	15	15
Adjusted R^2	0.261	0.289

Dependent variable is the log differential.
OLS regressions reported.
Unit of observation is the market-period.
Robust standard errors clustered by labor market.
Controls included for the risk preferences of managers and workers.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

3.3. Are differentials influenced by worker mobility?

We next examine whether the ability of workers to select their firm leads, as predicted, to smaller differentials. This result is confirmed in Table 2. The first column of Table 2 presents the estimates of an OLS regression model in which the differential is regressed on a dummy for whether costs are low. Consistent with the theoretical model presented in 2.1, we control for the risk preferences of the workers and managers. As predicted, we see that the differential is significantly smaller in the Low Cost sessions ($p < .01$). The next column includes a dummy variable indicating whether the Risky Firm manager selects the piece rate first in the current period. This models yields similar results and we note that the differential is smaller when the Risky Firm manager chooses first and the Safe firm manager is able to best respond. Consistent with the emergence of a stable equilibrium differential, the order in which managers set piece rates ceases to be significant in later

[9] Even treating each labor market as a single observation (i.e., averaging across periods), the difference remains significant at the $p = 0.002$ level in both the High Cost and Low Cost treatments.

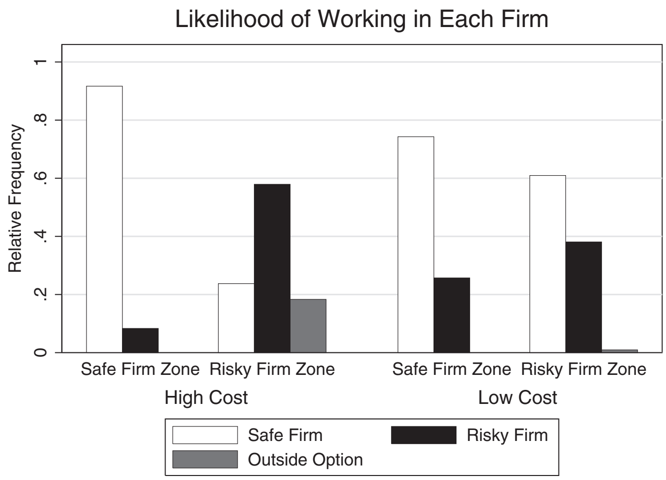

Fig. 4. Relative frequency of joining firm.

periods. As an additional robustness check, we regress the differential on session dummies to control for session-effects. In pairwise comparisons across sessions, we find no differences in sessions within a treatment and significant differences in all but one comparison across treatments, and therefore conclude that our result is robust across sessions.

3.4. *Do workers sort based on their tolerance for the disamenity?*

Finding that the wage gap associated with the risky disamenity shrinks when workers are mobile is consistent with the standard theory of compensating wage differentials. However, it does not confirm the hypothesized mechanism in that the differential shrinks because workers select into firms according to their risk preferences. To examine whether the hypothesized mechanism is correct, we first look at whether the commuting costs themselves are influencing worker movement into firms in the way that we predicted; we then turn to whether firm selection is driven by the elicited worker preferences.

Fig. 4 shows the relative frequency with which workers in the two zones select into each firm. On the left side, we see that workers in the High Cost treatment typically choose their home firm. This is particularly true of workers in the Safe Firm zone, who choose the Safe Firm over 90 percent of the time and never choose the outside option, suggesting that the Safe Firm bosses understand that they need to pay a piece rate above 40. Workers who live in the Risky Firm zone occasionally choose the outside option or to commute. In the Low Cost treatment, in contrast, there is much less bias toward choosing one's home firm and the outside option is essentially never taken. Overall, only 16% of workers "commute" in the High Cost treatment while almost three times as many (43%) do when the cost of commuting is low ($p < 0.01$). It thus appears that the cost treatments worked as intended.

More importantly, we ask whether workers sort into firms on the basis of their risk attitudes, and whether this selection is muted when commuting costs are high. Table 3 presents a series of linear probability models investigating the workers' decisions to join the Risky Firm.[10] The dependent variable in each of these models is an indicator equal to 1 if the worker chose the Risky Firm in the period and standard errors are clustered at the level of the worker.[11] In all models we include as a regressor the piece rate differential. These estimates indicate that the workers respond to the differential: the higher the premium, the more likely the worker is to choose the Risky Firm. Additionally, as we would expect (and a Hausmann test confirms, $p < 0.01$), the workers are far more responsive to the differential when the cost of commuting is low than when it is high.[12] We also include a regressor indicating whether the worker was randomly assigned to the Risky Firm zone and, as expected, find that this assignment is strongly associated with the worker's choice of the Risky Firm when costs are high, while the effect is marginal when commuting costs are low.

We next consider whether our measures of workers' tolerance for the disamenity drive firm selection. The later columns in Table 3 include as regressors our two measures of (narrowly-defined) risk-aversion: the externally-validated survey question (Columns 3 and 4) and the participants' Risk Choice in the first lottery question (Columns 5 and 6). Workers in the Low Cost treatment who report higher levels of Risk Aversion are significantly less likely to choose the Risky Firm (Column 3). This effect is not significant when costs are high (Column 4), indicating that participants are less able to sort on this measure in the High Cost treatment. Next, we include the lottery chosen in the pure Risk Choice and find that, while workers who are unwilling to take risks in this instrument do show a slight preference for the Safe Firm, the preference is not strong enough to generate a significant result here or in any other specification. This result echoes the findings of Carpenter et al. (2011) and Carpenter and Cardenas (2013), both of which use an identical set of lottery choices, that the lottery chosen in the Risk Choice task alone is neither predicted by the DRD4 gene associated with risky financial decision making nor strongly predictive of outcomes. The final two columns include both risk measures as independent variables and produce similar estimates to Columns 3 through 6.

In light of the literature suggesting that the two variables derived from the full set of lottery choices (Ambiguity Aversion and Loss Aversion) are often stronger predictors of behavior, we additionally consider whether workers are sorting on the basis of these related risk attitudes. Table 4 once again presents estimates of linear probability models in which the dependent variable is 1 if the worker joins the Risky Firm, but focuses on workers' Ambiguity Aversion and Loss Aversion as potential determinants of firm choice. The first column indicates that workers in the Low Cost treatment who exhibit higher levels of Ambiguity Aversion and Loss Aversion are significantly less likely to choose the Risky Firm. Just as with the survey risk aversion measure, the effect is no longer significant when costs are high (Column 2). The final two columns include the survey risk aversion measure as a control and again provide a similar story: workers who exhibit low tolerance for risk in the survey measure, and, to a lesser extent, for loss and ambiguity, are less likely to join the Risky Firm when costs are low but there is no evidence of selection on any preference measure when costs are high.[13]

[10] As a robustness check we ran Table 3 using the logistic regressor and the results were substantively the same.

[11] Standard errors are clustered at the worker level, since workers do not directly interact or receive feedback on other workers' decisions. The sorting results hold if standard errors are instead clustered at the level of the labor market.

[12] Some readers will perhaps wonder whether the piece rate differential is an endogenous regressor. It is important to remember, however, that the firm managers set the piece rates, and therefore the differential, before workers choose where to work. Even if the current differential reflects *previous* worker location decisions, however, the consequences are limited: our estimates of the remaining coefficients are robust with respect to the exclusion of the differential.

[13] Returning to the question of whether our preference measures may be picking up the subjects' numeracy, rather than their underlying risk preferences, we note that controlling for the average number of addition problems that the subject solved over the course of the session does not affect any of the preference sorting results presented in Table 3 or Table 4 and discussed above.

Table 3
Sorting into Risky Firm.

	(1) Low Cost	(2) High Cost	(3) Low Cost	(4) High Cost	(5) Low Cost	(6) High Cost	(7) Low Cost	(8) High Cost
Differential	1.363***	0.437**	1.374***	0.430**	1.364***	0.422**	1.377***	0.427**
	(0.244)	(0.194)	(0.203)	(0.184)	(0.245)	(0.176)	(0.203)	(0.174)
In Risky Firm zone	0.124	0.496***	0.117	0.488***	0.129	0.509***	0.131*	0.521***
	(0.086)	(0.088)	(0.071)	(0.102)	(0.084)	(0.081)	(0.072)	(0.097)
Survey risk aversion			−0.100***	−0.013			−0.102***	0.015
			(0.025)	(0.039)			(0.024)	(0.046)
Risk choice					−0.004	0.027	−0.012	0.033
					(0.024)	(0.022)	(0.018)	(0.027)
Constant	0.056	−0.004	0.297***	0.037	0.066	−0.092	0.331***	−0.157
	(0.062)	(0.035)	(0.097)	(0.130)	(0.093)	(0.078)	(0.102)	(0.210)
Observations	420	480	420	480	420	480	420	480
R^2	0.186	0.302	0.256	0.304	0.186	0.313	0.257	0.314

Dependent variable is 1 if worker is in Risky Firm.
OLS regressions reported.
Risk Choice is the first lottery choice (1 - 6) and survey risk aversion is reported risk aversion on a 6-point scale
Unit of observation is the worker-period. Robust standard errors clustered by worker.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Sorting into Risky Firm.

	(1) Low Cost	(2) High Cost	(3) Low Cost	(4) High Cost
Differential	1.313***	0.447**	1.343***	0.441**
	(0.236)	(0.204)	(0.202)	(0.193)
In Risky Firm zone	0.157*	0.514***	0.131*	0.508***
	(0.087)	(0.083)	(0.076)	(0.096)
Loss aversion	−0.044*	−0.044	−0.033**	−0.043
	(0.022)	(0.028)	(0.016)	(0.028)
Ambiguity aversion	−0.070***	−0.015	−0.041***	−0.016
	(0.020)	(0.018)	(0.013)	(0.019)
Survey risk aversion			−0.087***	−0.010
			(0.024)	(0.038)
Constant	0.110	0.018	0.304***	0.048
	(0.071)	(0.037)	(0.104)	(0.132)
Observations	420	480	420	480
R^2	0.221	0.316	0.268	0.316

Dependent variable is 1 if worker is in Risky Firm.
OLS regressions reported.
Ambiguity and Loss Aversion are integers between −5 and 5, as reported in Table 1.
Unit of observation is the worker-period. Robust standard errors clustered by worker.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We therefore conclude that workers in the Low Cost treatment are sorting into firms on the basis of their attitudes toward the disamenity, while workers in the High Cost treatment are less able to do so, suggesting that the smaller differential we see in the Low Cost treatment is indeed the result of worker selection.[14] The differences in both behavior and differentials that we observe between our two mobility conditions support the standard labor economics conjecture that naturally occurring differentials are likely to be lower bounds if workers can sort based on their tolerance for the disamenity.

[14] As mentioned, the purpose of the High Cost treatment is to limit mobility, and therefore, selection. This said, there is actually some movement in the High Cost treatment. As one can see from the signs of the coefficients in Table 3, selection is working in the correct direction but the effect is not strong because it is too costly to commute. Further, approximately 20% of Risky Firm zone workers do select in that they opt out into self-employment as seen in Fig. 4. This effect is also not large, however, because Risky Firm managers set piece rates high enough to lure most workers out of their homes.

4. Discussion

The purpose of this study is to examine the theoretical conjecture that wage adjustments made by firms on one side of the labor market can accurately aggregate worker preferences (embodied in the trade-off made between consumption and a risky disamenity) on the other. Further, we examine whether the equilibrium wage structure in this setting is affected by worker mobility and sorting, as is also hypothesized in the theory of equalizing differences. It is important to note that it is not obvious that the market will succeed in doing this: worker preferences must guide the willingness to accept job offers and firm managers must react to the signals they receive from the workers and they must also react optimally to the wage offers of other firms elsewhere on the compensation-disamenity frontier.

To the surprise of some, perhaps, we find that the process works reasonably well – though not perfectly – in the frictionless markets that characterize our experiment. Very quickly a substantial compensating differential arises and persists because risky firms must pay more to attract risk averse workers out of the “home production” sector. While the firm and preference differences combine to generate a stable differential, competition between firms is not perfect inasmuch as the compensating differential would not be enough to make a risk neutral or risk averse worker indifferent between working at the two firms.

As for worker sorting, we find strong results that support the standard theory. Our workers reveal risk attitudes consistent with other studies employing the same elicitation technique and they choose jobs on the basis of these preferences. Less tolerant workers sort into the safe firm and more tolerant workers find employment with the risky firm. Interestingly, sorting appears to happen based on “risk-related” preferences, not just baseline risk attitudes. Worker attitudes toward ambiguity and losses also cause them to sort into the two firms. Regardless of exactly which preferences are aggregated through market dynamics, we find that sorting has a significant effect on our estimates of the differential. Because tolerant workers are willing to accept smaller premia to work at the risky firm and less tolerant workers are happy to work for lower wages at the safe firm, the equilibrium differential does shrink significantly. This suggests, as previous studies in the related literature caution, that unless sorting can be accounted for, estimates of the true average differential will be too low.

While laboratory experiments are advantageous for the reasons described above, it is important to note that there are also clear

Table 5
Bias due to common specification issues.

	(1) Experiment	(2) Unobservables	(3) Aggregation
Risky Firm	0.201*** (0.014)	0.145*** (0.011)	
Risky Sector			0.549*** (0.009)
Observations	854	854	900

Dependent variable is log reported wage. (Robust standard errors). OLS regressions reported.
Unit of observation is the worker-period for all workers (3) or all workers who did not choose self-employment (1 and 2).
Columns (1) and (3) include commuting costs, preferences and interactions.
In column (2) preferences and costs are not included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

limitations to this approach. In order to generate clean estimates of compensating differentials, our experimental design makes many necessary simplifications. For instance, our labor markets are small and each firm is capable of hiring the entire labor force. If the positions were scarce, one might expect compressed wages and differentials. Workers complete identical, independent tasks at each firm, such that firm-specific skills or complementaries in worker skills do not play a role. This decision was made to ensure that firms differed only in the risky disamenity. However, one might expect that workers who had previously acquired firm-specific skills would experience an additional type of commuting cost and thus that the targeting of specific workers for their skill sets would further magnify the differential. Further, managers are completely sheltered from the income risk that their employees face. We therefore view our laboratory results as complementary to the traditional labor economics estimates, and intended to demonstrate the basic mechanics.

We conclude with a methodological illustration of a broader, but under-appreciated, benefit of experimental methods. Our design is of course intended to overcome some of the challenges of estimating compensating differentials in the field, but it can also be used to “recreate” these difficulties and so better understand the biases in more traditional studies. In particular, we can re-estimate the same differential when the data set is censored, or partitioned, along various dimensions. Why does this matter? Estimates of compensating differentials based on observational studies inform a large number of public policies, including, for example, those that use the “value of a statistical life” to calculate costs or benefits, and economists must answer two distinct, but often conflated, questions: (1) Would the “correct” differential emerge, even in an idealized market? and (2) Could this differential be estimated with traditional data? Our results suggest that with the data available to most researchers, answers to either are, at best, tentative.

To this end, we start not with the “firm level data” used in previous sections, but instead with the individual compensation data that would be available to most researchers, and regress log piece rates accepted on worker and firm characteristics. The results are reported in Table 5. Column (1) includes all the desired controls - commuting costs, worker preferences and interactions. In this case, we recover the expected value of the “true” differential - that is, 20%. In column (2) we estimate the same differential but without the individual controls that are often unobserved or unavailable in observational research. In effect, this is the estimate that obtains when the researcher cannot control for sorting. As expected, this analysis underestimates the true risky firm premium by five and a half percentage points ($p < 0.01$) because it does not account for the differences between workers at the two firms. In column (3), on the other hand, we illustrate the potential for “aggregation bias.” If data were available to the researcher at the sectoral level - “coal mining” or “retail trade,” for example - and the two firms were combined into one sector (because each produces the same output with the same methods) - one could still estimate the differential relative to home production, a natural benchmark, perhaps the most common empirical specification in the literature. Consistent with Dorman and Hagstrom (1989), the differential is dramatically overestimated. Our results should therefore be viewed as a cautionary note by those working with conventional datasets.

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