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Evidence from a Field Experiment with Scientists



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PROFESSIONAL IDENTITY AND THE GENDER GAP IN RISK-TAKING EVIDENCE FROM A FIELD EXPERIMENT WITH SCIENTISTS

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ABSTRACT

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The gender gap in risk-taking is often used to explain differences in labor market outcomes. Some studies, however, suggest that this gender gap does not extend to professional contexts. This paper examines potential drivers of the gender gap in risk-taking, comparing the professional context of academia to a private setting. We draw on identity economics, which posits that individuals form multiple identities that moderate behavior across contexts. In an online field experiment with 474 scientists we vary the salience of the professional or private identity. We find that the gender gap in risk-taking is mediated when the professional identity is salient. We identify the switching of identities by females as an explanation. Our results suggest that if the gender gap in risk-taking is driven by selection, the selection is not (only) along risk-aversion, but (also) along the ability to switch between identities and to adapt to prevailing norms. This provides new insights for the discussion on gender, risk-taking and labor market policies, and suggests an important role for mentoring programs.

Keywords: Gender, risk-taking, identity, priming, labor market, field experiment JEL classifications: J16, D81, C93

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1. Introduction

Men and women are not equal. At least they are not equally paid and they are not equally represented in leadership positions in business, politics and academia. There are only 23 female CEOs in Fortune 500 companies (Bellstrom, 2015), 21 female senators in the 2017 US Senate (www.senate.gov) and only 28 percent of all full professors in the United States are female (National Center for Education Statistics, 2016). In spite of the strong efforts made by many countries to increase gender income equity, there is still a mean gender wage gap of approximately 15% in OECD countries (OECD, 2016).

Gender gaps have been mainly explained by differences in human capital accumulation and discrimination (Bertrand, 2011).¹ More recently, the focus has shifted to include differences in preferences between females and males, especially with respect to risk-taking, social preferences and competitiveness (Azmat and Petrongolo, 2014; Croson and Gneezy, 2009), suggesting that such differences explain part of the observed gender gaps. In this paper, we focus on the key aspect of individual risk-taking, as the gender gap in competitiveness may also be driven by risk attitudes (van Veldhuizen, 2016).²

While the majority of studies show that females take fewer risks than males (see Croson and Gneezy 2009 for on overview), the strength of gender differences seems to be context-dependent. In particular, a number of studies suggest that the gender gap in risk-taking does not extend to or is mediated in the professional context (Croson and Gneezy, 2009).³ This may be driven by a selection effect – competitive and risky work environments may deter a relatively large share of females –, or by social learning and adaptation to prevailing norms and expected behavior in professional contexts. There is evidence for

¹ Based on decomposition methods, Boll et al. (2016) show that a large part of the gap remains unexplained.

² Gender differences in competitiveness tend to result from differences in confidence, in attitudes towards competition and societal conventions (Andersen et al., 2013; Booth and Nolen, 2012; Gneezy et al., 2009; Niederle and Vesterlund, 2007, 2011). Trying to decompose the drivers of competitiveness, van Veldhuizen (2016) suggests that the gender gap in competitiveness might be largely driven by a combination of risk attitudes and overconfidence. This stresses the enduring importance of risk preferences for gender gaps.

³ For example, Atkinson et al. (2003) study mutual fund managers and find no gender-related differences in risk-taking. Johnson and Powell (1994) study a managerial sub-population and find no difference between males and females that would be related to risk preferences either. While Dwyer et al. (2002) still find that females take fewer risks than males in mutual fund investments, this risk-behavior gap is significantly reduced when controlling for financial investment knowledge. Adams et al. (2012) find that for board members, female directors are even more risk-seeking compared to male directors. Still, Beckman and Menkhoff (2008) as well as Olsen and Cox (2001) find that females take fewer risks than males for professional investors and fund managers, respectively. Schubert et al. (1999) show that gender-related differences in risk-taking are greatly reduced when the choices are framed as an investment problem compared to an abstract specification.



both channels: experimental economic evidence on the selection or sorting effect from the lab (e.g. Niederle and Vesterlund, 2007) and the field (Buser et al., 2014; Flory et al., 2014), as well as evidence that the (work) environment shapes behavior (e.g. Cohn et al., forthcoming; Booth and Nolen, 2012). However, it remains an open question whether the observed gender gap in risk-taking is driven by a selection effect, a permanent environmental adaptation effect, or whether individual risk-taking behavior differs between individual's professional and private identities.

In this paper, we experimentally examine potential drivers of the gender gap in risktaking by comparing risk-taking behavior of scientists whose professional identity is made salient and scientists whose private identity is made salient. Our analysis suggests a new mechanism to explain why the gender gap in risk-taking may be smaller in professional contexts: females may select themselves into more risky jobs based on the ability to adapt to different environments. This mechanism can be viewed as a combination of the selection and environmental adaption channels and would imply that successful females are able to act in accordance with professional norms that may require higher risk-taking without giving up the comparably risk-averse behavior in private settings.

Our analysis draws on the theory of identity (Akerlof and Kranton, 2000), which posits that individuals may form multiple identities that moderate behavior across different contexts. While there seem to be differential gender-related stereotypes in private life – females are *perceived* to be more risk-averse (Ball et al., 2010) and they *act* more financially risk-averse (Charness and Gneezy, 2012)⁴ – there is usually a common idea of 'professional behavior'.⁵ If behavior is affected by prescribed behavior, this may explain why gender differences in risk-taking are often found to be smaller in professional environments.

To shed light on the drivers of the gender gap difference in risk-taking between professional and private settings, we perform an online field experiment with 474 scientists, including 278 males and 196 females. We make use of the priming technique that uses environmental cues to activate a certain identity and make it temporarily more salient (e.g.

⁴ See Bordalo et al., (2016a; 2016b) for more general results on stereotypes and beliefs about gender.

⁵ The findings of Bursztyn et al (2017) even suggest that 'private' considerations may be the reason for still observed gender differences in professional behavior.



Benjamin et al., 2010).⁶ Specifically, we experimentally vary the salience of the private or professional identity in two treatments using nine questions relating to the professional or private context. For example, subjects in the professional identity treatment are asked "Where did you last go to for a conference/workshop?", while subjects in the private identity control treatment were asked "Where did you last go on holiday?". We use a standard, incentivized risk elicitation task (Binswanger, 1981; Dave et al., 2010; Eckel and Grossman, 2002), where subjects are asked to choose one out of six lotteries that increase in riskiness, from a safe option to a lottery that elicits risk-seeking behavior.⁷

In accordance with the literature, we find that females take fewer risks compared to males. We also confirm the general finding that risk-taking decreases with age for male scientists (see e.g. Dohmen et al., forthcoming; Grubb et al., 2016; Mather et al., 2012), independent of the treatment. In contrast, there is a clear treatment effect for females: In the professional identity treatment, a higher proportion of females display risk-seeking behavior. Furthermore, risk-seeking as well as risk-taking behavior increases with age for female scientists in the professional identity treatment. As a result, the gender gap in risktaking decreases with academic age and fully closes for senior scientists when their professional identity is salient.

Our results paint a more nuanced picture concerning the explanation that relatively risk-averse females leave risky professional contexts such as academia. In our experiment, female scientists still take fewer risks when their private identity is salient. In turn, if the professional identity is made salient, gender-related differences in risk-taking are smaller or insignificant. Our findings thus suggest that if the gender gap in risk-taking is driven by selection, the selection is not (only) along general risk-aversion, but (also) along the ability to switch between private and professional identities and to adapt to prevailing norms.

⁶ Cohn and Marechal (2016) provide a recent review of identity priming in economics and discuss how this builds on a previous substantial literature in social psychology. The first economic experiments on identity priming were Chen and Li (2009) as well as Benjamin et al. (2010). In general, there are two approaches to studying how behavioral measures differ across identities: artificially inducing certain identities, or studying the effect of identity priming in natural populations, such as bankers (Cohn et al. 2014), criminals (Cohn et al., 2015), or scientists, as in our study.

⁷ Our analysis is closely related to the study of Cohn et al. (forthcoming), who find that priming the saliency of professional identity causally affects bankers' decision-making under risk. They employ a different investment task to elicit risk preferences (cf. Gneezy and Potters, 1997). For bankers, the professional norm points towards more risk-averse behavior and the authors find no significant impact of gender. Our study is also related to Cadsby et al. (2013) who consider competitiveness of MBA-students when their professional identity is salient and find qualitatively similar gender-related results as we do for risk-taking.



Our study contributes to the literature in three ways. First, it examines whether the gender gap in risk-taking carries over to scientists. Second, it offers an explanation why the gender gap in risk-taking is mediated in the professional environment. We replicate the two findings that females take less risk than males, and that this gap is mediated in a professional context. We provide causal evidence that making either the private or the professional identity salient has an influence on the risk-taking of females and thus on the gender gap in risk-taking. Finally, we identify a new channel according to which females may select in or out of professional environments: the ability to switch between private and professional identities to better adapt to differences in the environments' prescribed behaviors. This provides new insights for the discussion on gender, risk-taking and labor market policies: While a simple selection effect might necessitate quotas to achieve professional gender equity – as is the policy goal in many countries and contexts – our findings point towards an important role for (additional) mentoring programs.

2. Experimental Design and Hypotheses

To study the risk-taking behavior of scientists under professional and private identity priming, we conducted an online field experiment with members of an international scientific organization in the summer of 2016. The members are predominantly natural scientists, with a focus on the marine environment.⁸

The administrative office of the scientific organization provided an e-mail list of their 1930 members. We contacted all members by e-mail and invited them to participate in a short online survey that consisted of ten pages and took about 15 minutes to complete. We stated that participation would be compensated with 25 on average (equivalent to 27\$ at the time of the experiment) and that individual responses would be kept confidential. Upon clicking the link to the online survey in the invitation e-mail, subjects were assigned to one of two treatments by the computer: either the professional identity treatment (abbreviated *Professional*) or the private identity treatment (*Private*). A preamble page provided further details on the experiment and the mode of payment (Amazon vouchers). The survey then began with simple descriptive questions on age, gender and nationality. This was followed by our manipulation that consisted of nine questions either relating to their professional identity (*Professional*) or relating to their private



identity (*Private* treatment). The purpose of these questions was to make the subjects' professional identity, and associated prescribed behavior, more salient in *Professional* as compared to *Private*.

In an effort to reduce potential confounding due to priming effects that are unrelated to the private or professional identity, we designed the questions to be as similar as possible in terms of content and context, (see Table 1 for a list of all priming questions; cf. Figures A.1 and A.2 in Appendix A for the screenshots from the online survey).⁹

Professional identity treatment	Private identity treatment		
Who is your current employer?	What is your current city of residence?		
How many years have you worked for this institution?	How many years have you lived in your current accommodation?		
Do you have a tenured position?	Are you married?		
How large is your direct working team (yourself included)?	How large is your direct family (yourself included)?		
Where did you last go to for a conference/ workshop?	Where did you last go on holiday?		
In which year did you start your PhD?	In which year did you kiss the first boy/girl?		
At what time do you usually arrive at the office?	At what time do you usually arrive at home?		
What activity in your work do you enjoy the most?	What activity in your leisure time do you enjoy the most?		
How satisfied are you with your work in general?	How satisfied are you with your life in general?		

Table 1: Identity Priming Questions

The identity manipulation was followed by three experimental tasks that were always presented in the same order.¹⁰ In this paper we focus on the first task, an established incentivized risk preference elicitation task based on Binswanger (1981) and Eckel and Grossman (2002). This task presents subjects with six different choice options in the form of lotteries. Subjects had to decide on their most preferred lottery (see Table 2, subjects only saw the information in the first three columns; cf. Appendix A, Figure A.3, for a screenshot from the online survey). Each option is related to two possible payouts, either the amount stated in columns 2 (Payment A) or 3 (Payment B) of Table 2, each occurring

⁸ We do not report the name of the scientific organization to assure respondents' anonymity.

⁹ Besides these nine priming questions, the only other difference between treatments was that on the preamble page we stated that the study was on either on "Work [Life] satisfaction, including individual attitudes and behavior" in Professional [Private].

¹⁰ Once a subject had completed a task and proceeded to the next page, it was not possible to switch back. The initial risk task was followed by a coin toss truth-telling task, which we analyze in a companion paper (Drupp et al., 2017). Finally, we posed a hypothetical social time preference task.



with 50% probability. The next column of the table indicates the expected payout for each option. For options 1 to 5, the expected payout increases with the standard deviation of the gamble, depicted in the fifth column. Options 5 and 6 have the same expected payout, but option 5 has a smaller standard deviation compared to option 6. In particular, we see that there is a qualitative difference between options 1 to 5 and 6. While choosing options 1-5 indicates risk-averse behavior, a choice of option 6 indicates risk-seeking behavior (or at least risk-neutrality). The risk choices can also be related to a range of Constant Relative Risk Aversion (CRRA)-parameters (see last column in Table 2).¹¹

Choice Options	Payment A (in €)	Payment B (in €)	Expected payout (in €)	Standard deviation	CRRA range, $U(x) = \frac{x^{1-r}}{1-r}$
1	7	7	7	0	3.460 <r< td=""></r<>
2	6	9	7.5	1.5	1.161 <r<3.460< td=""></r<3.460<>
3	5	11	8	3	0.706 <r<1.161< td=""></r<1.161<>
4	4	13	8.5	4.5	0.499 <r<0.706< td=""></r<0.706<>
5	3	15	9	6	0 <r<0.499< td=""></r<0.499<>
6	2	16	9	7	r <0

Table 2: Description of the Risk Choices in the Experimental Task

Following the experimental tasks, participants were asked to complete a short followup survey that included a word-completion task designed to provide an implicit measure of how well the identity priming manipulation had worked (cf. Cohn et al., 2014; Kahneman, 2013). Subjects were presented with eight word fragments and they were asked to fill in the gaps with letters to form existing words. The idea is that when the professional identity is salient other words come to the participants' mind as compared to when the private identity is salient. For example, they were shown the word fragment "j o u r_ _ _", which they could complete with the word "journal" that scientists would frequently encounter in their professional lives, or the word "journey," which might be more salient to those in the

¹¹ In line with the previous literature (e.g. Eckel and Grossman, 2008), the table shows strict inequalities and excludes CRRA-parameters for which two neighboring gambles yield the same expected utility. The idea is as follows: the probability that a given number represents the preferences approaches zero. Thus, also the probability that the six excluded values represent preferences approaches zero. This allows relating preferences to non-overlapping CRRA-parameter ranges. Non-overlapping ranges also allow making the



Private treatment.¹² We classified all completed words and either assigned the number 1 to words related to the professional work identity or 0 to words classified as related to a private life. Words that could not be classified as relating to either context or words without actual meaning were coded as missing.

Together with the payoff from the second task (a truth-telling task), which ranged from 0 to 20, and a 5 compensation for completing the short follow-up survey, each subject could earn up to 41 c. The payoff from the risk task was revealed after subjects had completed the short follow-up survey.¹³

A theoretical framework incorporating identity considerations can facilitate a better understanding of what may drive the gender gap in risk-taking. Our framework builds on Akerlof and Kranton (2000) and Benjamin et al. (2010) and is static in nature.¹⁴ Identity models are based on the idea that several social categories – like being a woman, a man, a parent, a teacher – are available and that each social category comes with a stereo-typical or prescribed behavior. Individuals identify with certain social categories and derive dis-utility when they deviate from the prescribed behavior, as this means a loss of identification.

Let there be *C* different social categories, indexed by j = 1, ..., C and let \hat{A}_j denote the prescribed behavior in category *j*. Individual *i* assigns weight $w_i(s_{ij})$ on complying with the prescribed behavior of a category based on the strength of identification with that category s_{ij} , with $w_i(s_{ij}) \ge 0$, $\sum_{j=1}^{C} w_i(s_{ij}) = 1$. An increase in the identification – such as caused by priming – usually increases the weight assigned to that category, $\frac{\partial w_i}{\partial s_{ij}} \ge 0$. ¹⁵ If the identification with a social category is zero, $s_{ij} = 0$, the weight assigned to the social category is also zero, $w_i(0) = 0$, rendering it behaviorally irrelevant.

distinction between risk-averse and risk-seeking behavior, as in general, option 6 could also be chosen by a risk-neutral person (while no risk-averse person would do so).

¹² The first two of the eight word fragments ("_ a l k" and "_ o o k") had no unambiguous professional science interpretation. These two were meant as an easy start for participants and served, following Cohn et al. (2014, forthcoming), the purpose of disguising the purpose of the task. The other word fragments were: "_is_", "__ssion", "co_", "__ock" as well as "__per".

¹³ We also offered the possibility to donate fractions (in 10% steps) of their earnings to the charity 'Doctors Without Borders'. This donation option was not pre-announced and the donation decision could not have influenced risk-taking behavior.

¹⁴ Bénabou and Tirole (2011) develop a dynamic model of identity and one could use their idea of investing into certain identities to make a dynamic version of our model. Stets and Burke (2000) discuss `identity' from the perspective of social psychology.

¹⁵ As discussed in Benjamin et al. (2010) the second derivative of w_i may take either sign. When an individual already strongly identifies with a category, priming could have a stronger effect (w'' > 0), or also a lower effect if the individual is already saturated with that identity (w'' < 0).



We assume a two-stage process: First, individuals choose their identification with different social categories in order to maximize some long-run utility function. In other words, individuals have a baseline or steady state identification with the different social categories that determine their general behavior. Second, taking this baseline identification as given, individuals choose their short-run action to comply with their general identity as well as the environmental context. A specific context or prime may then induce the individuals to deviate from this baseline behavior to shift more towards the relevant prescribed behavior. The focus here is only on this second stage, i.e. on the short-run reaction to environmental cues.

Given the choices of baseline identification with the different social categories, let the individual i choose (short-run) action a_i in order to maximize the following instantaneous utility function

$$U(a_i) = -\sum_{j=1}^{C} w_i(s_{ij}) \left(a_i - \hat{A}_j\right)^2$$
(1)

When several social categories are important and prescribed behaviors in these social categories deviate from one another, a short-run identity conflict arises. The optimal action a_i^* is then a weighted average of the prescribed behaviors in the different social categories,

$$a_{i}^{*} = \sum_{j=1}^{C} w_{i}(s_{ij})\hat{A}_{j}$$
(2)

Three remarks are in order. First, although an identity conflict may reduce shortrun utility, the identification choices are - per assumption - optimal in the long-run perspective. Second, as individuals assign different weights on complying with prescribed behaviors, the observed actions of the individuals also differ. Third, a strong reaction of the weighting to the prevalent environment may induce that temporarily only one social category is of importance, which increases instantaneous utility relative to a situation with an identity conflict.

We now turn to our experiment on whether or not the saliency of the professional or the private identity of a person influences risk taking. In terms of the model, risk-taking relates to the observed action a_i , with a higher a_i denoting more risk-taking. As the identification with other social categories is not impacted, we reduce the model to only include two possible identities: Private [PRIV] and Professional [PROF]. One can interpret each identity as a bundle of social categories and prescribed behaviors. Accordingly, the overall prescribed behavior may be gender specific. For gender g, we also simplify and only



consider either male, denoted m, or female, denoted f. Equation (2) then becomes

$$a_i^g = w_i \left(s_{i, PROF} \right) \hat{A}_{PROF}^g + \underbrace{\left(1 - w_i \left(s_{i, PROF} \right) \right)}_{w_i \left(s_{i, PRIV} \right)} \hat{A}_{PRIV}^g \,. \tag{3}$$

Priming a certain identity means that the identification strength s_{ij} with the corresponding social category is temporarily increased. In other words, we are interested in the marginal impact on risk-taking of making the professional identity more (or less) salient

$$\frac{\partial a_i^g}{\partial s_{i,PROF}} = \frac{\partial w_i}{\partial s_{i,PROF}} \left(\hat{A}_{PROF}^g - \hat{A}_{PRIV}^g \right) \tag{4}$$

In order to form clear predictions based on our model, we make three assumptions. First, Bursztyn et al. (2017) suggest that possible differences in professional behavior between males and females are driven by private (i.e. marriage) considerations. We thus assume that there is a gender-invariant idea of 'professional behavior': $\hat{A}_{PROF}^{f} = \hat{A}_{PROF}^{m} = \hat{A}_{PROF}$. Behavioral codes related to risk-taking in the private context in turn may be gender-specific. Females are *perceived* as being less risk-taking (Ball et al., 2010), which may be related to females being *expected* to act less risk-taking. We therefore, second, assume that $\hat{A}_{PRIV}^{f} \neq \hat{A}_{PRIV}^{m}$, and especially that prescribed risk-taking behavior in the private context is such that females are deemed to take fewer risks than males: $\hat{A}_{PRIV}^{f} < \hat{A}_{PRIV}^{m}$. As academia, which is regarded as a relatively risky field of employment (e.g. Fox and Stephan, 2001),¹⁶ has been and still is a male-dominated profession (Knights and Richards, 2003; West et al., 2013), males may have predominantly shaped professional norms and customs with respect to risk-taking behavior. We thus, finally, assume that $\hat{A}_{PROF} \approx \hat{A}_{PRIV}^{m}$, which implies via the second assumption that $\hat{A}_{PROF} > \hat{A}_{PRIV}^{f}$.

Aggregating over all i = 1, ..., N individuals of a population yields the mean risk choice $\bar{A} = \frac{1}{N} \sum_{i=1}^{N} a_i$, which can be disaggregated for different groups within a population. For instance, we denote the mean risk choice of females in the *Professional* identity treatment as \bar{A}_{PROF}^{f} . Optimal risk-taking as implied by our model and given our assumptions predicts the general finding that, on average, females are more risk-averse than males, i.e. $\bar{A}^m > \bar{A}^f$ (e.g. Croson and Gneezy, 2009; Charness and Gneezy, 2012). Our model also predicts that females make more risky decisions when their professional identity

¹⁶ Job prospects are uncertain for untenured researchers, as tenured positions are scarce, returns to potentially ground-breaking research projects are high, but very risky, and one could argue that science is competitive.



is salient compared to the private identity, i.e. $\bar{A}_{PROF}^{f} > \bar{A}_{PRIV}^{f}$. Also, Equation (4) and our assumption that $\hat{A}_{PRIV}^{f} < \hat{A}_{PRIV}^{m}$ imply that the impact of professional identity priming, i.e. increasing the identification with the professional environment, is more pronounced for females than for males. Professional identity priming should therefore diminish the gender gap in risk-taking.

What does our simple model imply about the different channels affecting the (dis)appearance of the gender gap in risk-taking in professional versus private contexts? The difference between \hat{A}_{PRIV}^{f} and \hat{A}_{PROF} means a utility loss for females. Therefore, leaving science to work in a different sector in which the prescribed behavior is more similar to the prescribed behavior in *Private* may increase utility. According to such possible self-selection, the following 'types' of females would stay in academia:

First, we could observe females in academia who attach a lot of weight to the professional identity (high w_i) and thus stick to one form of risk-taking behavior without experiencing a large utility loss.¹⁷ In this case, risk choices should be similar across treatments. A high weight on the professional identity and high risk-taking of female scientists would correspond to the standard selection channel. One would observe a gender gap in risk-taking for the general population but not for scientists (neither when the private nor the professional identity is more salient).

Second, we could observe females in academia whose preferences are shaped by the academic environment and whose weights, $w_i(s_{i,PROF})$, on complying with the professional norm might increase with their academic age. If this environmental adaptation effect was the driver, risk choices of female scientists would develop with their exposure to the work environment, i.e. academic age, such that their overall risk-taking – in the private and in the professional environment — would increase over time. This adaptation to the work environment would observationally go against the general finding that risk-taking behavior reduces with age. Risk-taking of female scientists might therefore remain constant – as the age and environmental adaptation effects cancel each other out –while males' risk-taking would decline with age. The gender gap in risk taking would be especially large for young scientists. Controlling for age, risk choices should be similar across treatments.

¹⁷ Note that in terms of the model the same prediction about a context-independent risk-taking behavior would also occur for those females that attach very little weight to the professional identity.



Finally, we could observe females in academia whose weights, $w_i(s_{i,PROF})$, on complying with the professional norm are (strongly) impacted by a change in the strength of identifying with the professional environment, $s_{i,PROF}$. In this case, we expect the behavior to differ between the two priming treatments. In particular, we expect $\bar{A}_{PROF}^{f} > \bar{A}_{PRIV}^{f}$, and accordingly a diminished gender gap in risk-taking when the professional identity is made salient.

In order to test our model and to learn more about the drivers of the gender gap, we now examine risk-taking of female and male scientists in our two identity treatments.

3. Results

We have received 599 responses to the survey, amounting to a response rate of more than 30%.¹⁸ Our results are based on 474 scientists who have completed the risk task.¹⁹ Figure 1 depicts a world map, in which the red balloons indicate the locations of the participants. Participating scientists come from all major continents, and predominantly from Europe and North America.



Figure 1: Map of the World With the Locations of Our Subjects (Red Balloons)

¹⁸ Overall, 946 individuals clicked on the link to our study. Appendix B investigates potential response bias and the balance across treatments. We find that males appear to drop out of Professional more frequently than out of Private. This attrition on the part of males does not appear to be problematic for our subsequent findings.

¹⁹ We dropped 10 observations because they responded more than once as well as one observation because we could identify her as still being a master student.



Before we turn to analyzing the decisions in the risk task, we test whether our implicit measure of identity priming using the word completion task indicates that priming has been successful. For each of the 429 subjects that have filled out some of the to-becompleted words, we aggregate over the given numbers assigned to completed words for the six potential word checks (1 for words associated with professional life, 0 for words associated with private life) and then compare the mean value of these aggregate numbers across the two treatments. Furthermore, we create an index that captures the relative frequency of mentioning words associated with professional life. We find that the mean number of 'professional' words, such as "journal", "paper" or "session", is higher in *Professional* (2.87 words) as compared to the 'professional' words in *Private* (2.65 words, two-sided t-test: p = 0.060). Furthermore, the relative frequency of mentioning words associated with professional words in *Private* (2.65 words, two-sided t-test: p = 0.060). Furthermore, the relative frequency of mentioning words associated to the 'professional' words in *Private* (2.65 words, two-sided t-test: p = 0.092). This provides some supportive evidence that our *Professional* treatment was able to make the professional scientific identity of our subjects more salient compared to the *Private* treatment.

We turn to examining the risk choices of scientists. For this purpose, we assign the scale in the first column of Table 2 to the choices, ranging from 1 to 6. First, we examine whether there is an overall priming effect on overall mean risk behavior \overline{A} . We find that the mean risk choice is $\overline{A}_{PRIV} = 3.96$ compared to $\overline{A}_{PROF} = 3.82$. A two-sided Mann-Whitney test does not reject the null hypothesis of equal risk-taking in the two treatments (p > 0.10). We therefore cannot confirm the hypothesis that scientists are generally willing to take greater risks in the professional environment.

Examining gender differences, we find that the average risk choice of females is $\bar{A}^{f} = 3.40$ compared to $\bar{A}^{m} = 4.22$ for males. A two-sided Mann-Whitney test rejects the null hypothesis of equal risk-taking in favor of greater risk-taking of males at p < 0.01. This finding confirms the general result in the literature that females are more risk-averse than males.

As there is a qualitative difference between risk choices 1 to 5 (indicating riskaverse behavior) and choice 6 (indicating risk-seeking), and since risk-seeking behavior may



be an important trait of scientists, we now examine risk-seeking behavior more closely.²⁰ Figure 2 depicts the frequencies of risk-seeking choices by treatment and gender. Differences between males and females in risk-seeking behavior are significant (chi-squared test, p < 0.01), i.e. more males exhibit risk-seeking behavior as compared to females. We observe in particular that there is a substantially higher frequency of risk-seeking choices of male scientists as compared to other subject pools (for instance, Dave et al., 2010; Khadjavi, forthcoming).

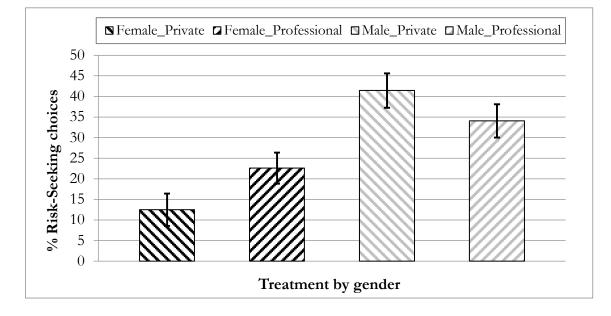


Figure 2: Risk-seeking Choices for the Different Gender-treatment Combinations

As expected, we do not find a treatment effect in risk-seeking behavior among males (34.06% in *Professional* vs. 41.43% in *Private*, two-sided chi-squared test, p > 0.10). However, we find a treatment effect for females. The share of females in *Professional* who make risk-seeking choices is larger than the share in *Private* (22.58% vs. 12.50%, two-sided chi-squared test, p < 0.10). That is, more females make risk-seeking choices in *Professional* compared to *Private*. We summarize:

Result 1. More female scientists make risk-seeking decisions when their professional identity is salient compared to when their private identity is salient.

²⁰ The only other study on professional identity priming and risk-taking behavior, Cohn et al. (forthcoming), elicited risk-taking behavior on a more continuous scale, using the investment task by Gneezy and Potters (1997) without the possibility to distinguish risk-averse from risk-seeking behavior.



We complement our treatment tests with a regression analysis to control for other observable characteristics while estimating the impact of our treatments on risk choices. Besides the risk choices, the gender and our identity priming treatments, we collected data on age, whether the subject is a tenured scientist and on the location of the subject for both treatments. Table 3 presents the results of Logit (the likelihood of a risk-seeking decision) and Tobit (from 1 to 6) estimations for decision-making under risk, respectively.

	Logit regression	Tobit regression
Independent variables	Dependent variable: Risk-seeking choice (=1 if risk-seeking choice, else 0)	Dependent variable: Risk choice (from 1 to 6)
Female	-0.28***	-2.18***
(dummy, female=1)	(0.07)	(0.50)
Professional treatment	-0.06	-0.42
(dummy, Professional=1)	(0.05)	(0.40)
Female x Professional	0.19*	1.06*
(interaction term)	(0.11)	(0.63)
Tenured	-0.00	0.16
(dummy, tenured=1)	(0.05)	(0.34)
Age	-0.00	-0.04**
(continuous)	(0.00)	(0.02)
European	0.01	-0.33
(dummy, European=1)	(0.05)	(0.37)
Observations	457	457

Table 3: Regression Analysis of Risk Choices and Risk-Seeking Behavior

Note: *Private* is the baseline of the estimations. The lower [upper] limit of the Tobit is 1 [6]. Both columns show marginal effects. Standard errors in parentheses, statistical significance: *p<0.10, **p<0.05, ***p<0.01.

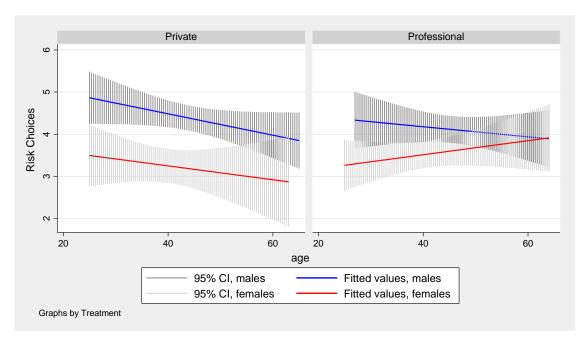
Again, we do not find a general treatment effect for the risk choices (including females and males) between *Professional* and *Private*. We do, however, identify a positive interaction term for females in *Professional* and thereby confirm Result 1 and extend it to risk-taking behavior more generally: More females in *Professional* make risk-seeking choices (Logit regression) and are less risk-averse (Tobit regression) compared to females in *Private*. The composite effect of 'Female' and 'Female x *Professional*' in both regressions remains significantly different from zero (p < 0.05 for both tests). Hence, females in *Professional* still exhibit less risk-seeking behavior compared to males, although the difference is smaller. We summarize:

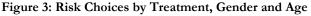
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Result 2. The gender gap in risk-taking is diminished if the professional identity is salient.

Interestingly, our Tobit regression in Table 3 reports a negative correlation between age and risk-taking. We therefore examine whether our treatment effects are stronger for older, tenured scientists compared to younger scientists.





Note: The red (blue) lines depict the linear fits for females (males).

Figure 3 provides a graphical overview of how mean risk-taking behavior of males (blue lines) and females (red lines) changes with age across the two treatments for the age range 25-65. In *Private* we observe the common result that older individuals are less risk-seeking than younger ones (see, e.g. Dohmen et al., forthcoming; Grubb et al., 2016; Mather et al., 2012). We observe this direction almost parallely for females and males in *Private* without any mentionable overlap. However, for females in *Professional* we find that choices become more risky with age. If we split the whole sample at the median age (42 years), we find that junior and senior male scientists take greater risks than junior and senior female scientists respectively in *Private* (two-sided Mann-Whitney tests, for both p < 0.05). While we also find the usual gender gap in risk-taking for junior scientists in *Professional* (Mann-Whitney test, p < 0.01), the gap is completely closed for senior scientists



(p > 0.70). Likewise, and as age and tenured are highly correlated, we find no gender gap in risk-taking for tenured scientists in *Professional* (two-sided Mann-Whitney test, p > 0.40). This finally yields

Result 3. The gender gap in risk-taking is closed for senior scientists if the professional identity is salient.

4. Discussion and Conclusion

This study has investigated drivers of the gender gap in risk-taking by experimentally varying the salience of the professional identity in an online field experiment. To this end, we have focused on a particular labor market: academia. Our results confirm the gender gap in risk-taking found in the experimental literature also for scientists: On average, females are more risk-averse than males. Our identity-priming intervention reveals that more females make risk-seeking decisions when their professional identity is salient, while this is not the case for males. This leads to the finding that the general gender gap in risk-taking is reduced when the professional identity is salient. We further show that the gender gap in risk-taking is closed for senior scientists when the professional identity is salient.

Our findings paint a nuanced picture regarding the drivers of the gender gap in risk-taking. Our results can neither be explained by a simple story of sorting into risky occupations based on general risk preferences, as risk-averse females do not leave science in general. Nor can our results be explained by the hypothesis that the work environment shapes the general risk-preferences of (female) scientists, as risk-taking behavior differs between treatments. Instead, our findings can be viewed as being consistent with the literature on sorting (Buser et al., 2014; Flory et al., 2014) in a more subtle way: our evidence suggests a sorting that depends on identity considerations. Indeed, our results indicate that those females stay in academia who can adapt better to the prevailing professional norms and behavioral modes of higher risk-taking in a professional environment, while still complying with 'female' norms in the private context. Thus, our evidence also relates to recent findings that agents adapt their behavior to different environmental contexts related to the hypothesis that the work environment shapes



preferences (Booth and Nolen, 2012; Cohn et al., forthcoming; Gneezy et al., 2009; Leibbrandt et al., 2013).

While we are able to provide causal evidence regarding our priming treatments and related gender effects, our cross-sectional dataset is not able to clearly identify the exact mechanism leading to the gender gap for non-tenured scientists and its disappearance for older or tenured scientists. One would ideally trace subjects over a long time horizon to measure how their risk-taking changes and how this impacts the gender gap while (female) scientists select in or out of academia. We leave the question on gender differences in assigning weights to the different identities, and how this may change with age, to future research.²¹ We also leave the interlinkages of family planning, identity considerations and career planning for future research. Both aspects may hold important additional insights, but our data is not able to speak to those issues.

Our results have important implications for policies aimed at closing gender gaps in labor markets. First, our analysis suggests that one policy approach for attenuating or closing the gender gap in risk-taking would be to change prevailing norms and expected behaviors (either in the professional science context in general or specifically for females in the private context). Changing the prevailing norms may however be a rather slow process.²² Furthermore, risk-taking may also be warranted in science since uncertainty is inherent in the research process. Also from a social planner's perspective, it may not be optimal to induce norms of lower risk-taking in academia, as groundbreaking research is very valuable and often entails taking a considerable amount of risk.²³

Second, the identity-related behavior that our data reveals may be good news for gender equity, as there is evidence for long-run roots of preferences and associated economic behavior (e.g. Alesina et al., 2013; Becker et al., 2016). The long-run roots of preferences – possibly related to gender inequality – may be overcome by creating new social categories and identities. In turn, our results also shed light on the claim that the

²¹ Cinamon and Rich (2002), for example, identify three different profiles for the family-work importance: work is more important, family is more important, both are very important.

²² Besides changing prevailing norms in science, other mechanisms could be developed that would allow for better coping strategies, for example based on risk-diversification or risk-sharing that allow a more riskaverse person to undertake risky projects.

²³ For example, Rzhetsky et al. (2015) analyze millions of papers and patents on chemical relationships in biomedicine and conclude that increased risk-taking by scientists would considerably speed up the generation of new scientific discoveries.



world will be a different world if women ruled (see e.g. Funk and Gathmann, 2015). This may depend on the prevailing prescribed behaviors, and calls for further research.²⁴

Third, our results show that those females tend to stay in science that are good at adapting to the prevailing norms of a given context and thus at changing or 'switching' their identities from a private to the professional context. While part of this ability may be related to one's personality, it may still be possible to learn or improve this skill.

Finally, while our simple model assumes that the prevailing professional norm is known, this may not be the case in particular for younger scientists. So the prescribed behavior has to be discovered before the issue of compliance with the norm arises. This may matter especially for females, as the prescribed behavior in science seems to differ from the prescribed behavior for females in private settings more strongly than for males. These considerations suggest that programs focusing on facilitating a better understanding of the prevailing norms and expected behaviors in the professional context, and how to find and shape your own way of acting in a professional context, might be very helpful. Policy approaches to address these issues include, for example, mentoring programs, which have been shown to have a significant impact on the academic performance of participating females (Blau et al., 2010).²⁵

²⁴ See Ranehill and Weber (2017) for a recent study on how gender preference gaps impact policy outcomes.

²⁵ Examples in the economics context on such initiatives include, for example, the Standing Committee on Women in Economics of the European Economic Association, or the Committee on the Status of Women in the Economics Profession of the American Economic Association.



References

- Adams, R.B., & Funk, P. (2012). Beyond the glass ceiling: Does gender matter?. *Management Science*, 58(2), 219-235.
- Akerlof, G.A., & Kranton, R.E. (2000). Economics and identity. *Quarterly Journal of Economics* 115(3): 715-753
- Alesina, A., Giuliano, P., & Nunn, N. (2013). On the origins of gender roles: Women and the plough. *The Quarterly Journal of Economics*, 128(2), 469-530.
- Andersen, S., Ertac, S., Gneezy, U., List, J.A., & Maximiano, S. (2013). Gender, competitiveness, and socialization at a young age: Evidence from a matrilineal and a patriarchal society. *Review of Economics and Statistics*, 95(4), 1438-1443.
- Atkinson, S.M., Baird, S.B., & Frye, M.B. (2003). Do female mutual fund managers manage differently? *Journal of Financial Research*, 26(1), 1-18.
- Azmat, G., & Petrongolo, B. (2014). Gender and the labor market: What have we learned from field and lab experiments?. *Labour Economics*, *30*, 32-40.
- Ball, S., Eckel, C.C., & Heracleous, M. (2010). Risk aversion and physical prowess: Prediction, choice and bias. *Journal of Risk and Uncertainty*, 41(3), 167-193.
- Becker, A., Enke, B. & Falk, A. (2016). Ancient origins of the global variation in economic preferences. Mimeo.
- Beckmann, D., & Menkhoff, L. (2008). Will women be women? Analyzing the gender difference among financial experts. *Kyklos*, 61(3), 364-384.
- Bellstrom, K. (2015). GM's Mary Barra sets a Fortune 500 record for female CEOs. Fortune Magazine, website: fortune.com/2015/06/29/female-ceos-fortune-500-barra/[Last accessed: January 31, 2017].
- Bénabou, R. & Tirole, J. (2011). Identity, morals, and taboos: Beliefs as assets. Quarterly Journal of Economics, 126, 805-855.
- Bertrand, M. (2011). New perspectives on gender. Ed: Card, d. & Ashenfelter, O. Handbook of Labor Economics, 4, 1543-1590.
- Benjamin, D., Choi, J., & Strickland, J.A. (2010). Social Identity and Preferences. American Economic Review 100(4), 1913-28.
- Benjamin, D.J., Choi, J.J., & Fisher, G. (2016). Religious identity and economic behavior. Review of Economics and Statistics, 98(4), 617-637.
- Binswanger, H.P. (1981). Attitudes toward risk: Theoretical implications of an experiment in rural India. *Economic Journal*, 91, 867-890.
- Blau, F.D., Currie, J.M., Croson, R.T., & Ginther, D.K. (2010). Can Mentoring Help Female Assistant Professors? Interim Results from a Randomized Trial. *American Economic Review*, 100(2), 348-352.



- Boll, C., Rossen, A., & Wolf, A. (2016). The EU gender earnings gap: Job segregation and working time as driving factors. HWWI Research Paper No 176. Hamburg: HWWI.
- Booth, A.L., & Nolen, P. (2012). Gender differences in risk behaviour: Does nurture matter?. *Economic Journal*, 122(558), F56-F78.
- Bordalo, P., Coffman, K., Gennaioli, N., & Shleifer, A. (2016a). Stereotypes. *The Quarterly Journal of Economics*, 131(4), 1753-1794.
- Bordalo, P., Coffman, K., Gennaioli, N., & Shleifer, A. (2016b). Beliefs about Gender. NBER Working Paper No. 22972.
- Bursztyn, L., Fujiware, T. & Pallais, A. (2017). 'Acting Wife': Marriage market incentives and labor market investments. NBER Working Paper No. 23043
- Buser, T., Niederle, M., & Oosterbeek, H. (2014). Gender, competitiveness and career choices. *Quarterly Journal of Economics*, 129(3), 1409-1447.
- Cadsby, C. B., Servátka, M. & Song, F. (2013): How competitive are female professionals? A tale of identity conflict. *Journal of Economic Behavior & Organization*, 92, 284-303.
- Charness, G., & Gneezy, U. (2012). Strong evidence for gender differences in risk taking. Journal of Economic Behavior & Organization, 83(1), 50-58.
- Chen, Y., & Li, S.X. (2009). Group identity and social preferences. American Economic Review, 99(1), 431-457.
- Cinamon, R.G. & Rich, Y. (2002). Gender Differences in the Importance of Work and Family Roles: Implications for Work–Family Conflict. *Sex Roles* 47, 531–541.
- Cohn, A., Fehr, E., & Maréchal, M.A. (2014). Business culture and dishonesty in the banking industry. *Nature* 516, 86–89.
- Cohn, A., Maréchal, M.A., & Noll, T. (2015). Bad boys: How criminal identity salience affects rule violation. *Review of Economic Studies*, *82*(4), 1289-1308.
- Cohn, A., Fehr, E., & Maréchal, M.A. (forthcoming): Do professional norms in the banking industry favor risk-taking? *Review of Financial Studies*.
- Cohn, A., & Maréchal, M.A. (2016). Priming in economics. *Current Opinion in Psychology* 12, 17-21.
- Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, 47(2), 448-474.
- Dave, C., Eckel, C.C., Johnson, C.A., & Rojas, C. (2010). Eliciting risk preferences: When is simple better?. *Journal of Risk and Uncertainty*, 41(3), 219-243.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3), 522-550.
- Dohmen, T., Falk, A., Golsteyn, B., Huffman, D., & Sunde, U. (forthcoming). Risk attitudes across the life course. Forthcoming in *Economic Journal*.



- Drupp, M., Khadjavi, M., & Voss, R. (2017). Do Scientists Tell the Truth? Evidence from a Field Experiment. Mimeo.
- Dwyer, P.D., Gilkeson, J.H., and List, J.A. (2002). Gender differences in revealed risk taking: evidence from mutual fund investors. *Economics Letters* 76(2), 151-158.
- Eckel, C.C., & Grossman, P.J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior* 23(4), 281-295.
- Eckel, C.C., & Grossman, P.J. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior & Organization*, 68(1), 1-17.
- Fox, M.F. & Stephan, P.E. (2001). Careers of young scientists: Preferences, prospects and realities by gender and field. *Social Studies of Science*, 31 (1), 109-122.
- Flory, J.A., Leibbrandt, A., & List, J.A. (2014). Do competitive workplaces deter female workers? A large-scale natural field experiment on job-entry decisions. *Review of Economic Studies*, 82 (1), 122-155.
- Funk, P. & Gathmann, C. (2015). Gender gaps in policy making: Evidence from direct democracy in Switzerland. *Economic Policy* 30 (81): 141–81.
- Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *Quarterly Journal of Economics*, 112(2), 631-645.
- Gneezy, U., Leonard, K.L., & List, J.A. (2009). Gender differences in competition: Evidence from a matrilineal and a patriarchal society. *Econometrica*, 77(5), 1637-1664.
- Grubb, M.A., Tymula, A., Gilaie-Dotan, S., Glimcher, P.W., & Levy, I. (2016). Neuroanatomy accounts for age-related changes in risk preferences. *Nature Communications*, 7 (13822).
- Johnson, J.E., & Powell, P. L. (1994). Decision making, risk and gender: Are managers different?. British Journal of Management, 5(2), 123-138.
- Kahneman, D. (2013). Thanking, Fast and slow. Farrar, Straus and Giroux. New York.
- Khadjavi, M. (forthcoming). Deterrence works for criminals. *European Journal of Law and Economics*.
- Knights, D., & Richards, W. (2003). Sex discrimination in UK academia. Gender, Work & Organization, 10(2), 213-238.
- Mather, M., Mazar, N., Gorlick, M.A., Lighthall, N.R., Burgeno, J., Schoeke, A., & Ariely, D. (2012). Risk preferences and aging: The "certainty effect" in older adults' decision making. *Psychology and Aging*, 27(4), 801.
- National Center of Education Statistics (2016). Characteristics of Postsecondary Faculty. website: https://nces.ed.gov/programs/coe/indicator_csc.asp [Last accessed: January 31, 2017].
- Niederle, M., & Vesterlund, L. (2007). Do women shy away from competition? Do men compete too much?. *The Quarterly Journal of Economics*, 122(3), 1067-1101.



- Niederle, M., & Vesterlund, L. (2011). Gender and Competition, Annual Review of Economics, 3, 601-630.
- OECD (2016). Gender wage gap. website: https://www.oecd.org/gender/data/ genderwagegap.htm [Last accessed: January 31, 2017].
- Olsen, R.A., & Cox, C.M. (2001). The influence of gender on the perception and response to investment risk: The case of professional investors. *Journal of Psychology and Financial Markets*, 2(1), 29-36.
- Ranehill, E. & Weber, R.A. (2017). Do gender gaps affect policy outcomes? Mimeo, University of Zurich.
- Rzhetsky, A., Foster, J.G., Foster, I.T., & Evans, J.A. (2015). Choosing experiments to accelerate collective discovery. *Proceedings of the National Academy of Sciences*, 112(47), 14569-14574.
- Schubert, R., Brown, M., Gysler, M., & Brachinger, H.W. (1999). Financial decisionmaking: are women really more risk-averse? *American Economic Review* 89(2), 381-385.
- Shih, M., Pittinsky, T.L., & Ambady, N. (1999). Stereotype susceptibility: Identity salience and shifts in quantitative performance. *Psychological Science*, *10*(1), 80-83.
- Stets, J.E. & Burke, P.J. (2000). Identity Theory and Social Identity Theory. Social Psychology Quarterly, 63 (3), 224-237.
- van Veldhuizen, R. (2016). Gender differences in tournament choices: Risk preferences, overconfidence or competitiveness? WZB Discussion Paper No. SP II 2016-207.
- West, J.D., Jacquet, J., King, M.M., Correll, S.J., & Bergstrom, C.T. (2013). The role of gender in scholarly authorship. *PloS One*, 8(7), e66212.





Appendix A – Screenshots from the online survey

Figure A.1: Priming Questions for the Private Identity Treatment

What is your current city of reside	ence?						
How many years have you lived i	in your current acco	mmodation?					
Are you married?	Yes				No		
	O				0		
How large is your immediate fam	ily (yourself included	1)?					
Where did you last go on holiday?	,						
In which year did you kiss the fire	st boy/girl?						
At what time do you usually arriv	re at home?						
00:00 (XX:XX)							
Which activity in your leisure time	a da yau aniay tha m	oct2					
	e do you enjoy die in	USI:					
How satisfied are you with your li (1 to 9; not very satisfied to extremely	ife in general? / satisfied)						
1 2	3	4	5	6	7	8	9
Please proceed.							
							Continue



Figure A.2: Priming Questions for the Professional Identity Treatment	Figure A.2: Priming	g Questions for the	Professional Identity	Treatment
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Who is your current empl	oyer?						
How many years have you		institution?					
Do you have a tenured po							
O Yes	0	No					
How large is your direct w		urself include	ed)?				
Where did you last go to f	or a conference	/workshop?					
In which year did you star (please put 1111 if not applicable)						
At what time do you usua	Illy arrive at the	office?					
Which activity of your wo	rk do you enjoy	the most?					
							/
How satisfied are you with (1 to 9; not very satisfied to extre	mely satisfied)						
	2	3	4	5	6 	8	9
Please continue.							
							Continue



Figure A.3: Screen for the Risk Elicitation Task

Task	1		
How muc Specifical You decid Which of Your resu	h money you ly, each of t le on one of the two poss it will be sho	a gain depend he six option the options a ble payoffs y	arn additional money. Is on your choice for one of six opt ns contains two different possibl nd will then obtain either payment. I'ou receive is random and is based of the survey.
Option	Payment A	Payment B	Your Choice (please: make exactly one cross)
1	7.00€	7.00€	0
2	6.00€	9.00€	0
3	5.00€	11.00€	0
4	4.00€	13.00€	0
5	3.00€	15.00€	0
6	2.00€	16.00€	0



Appendix B – Testing for Response Bias

Laboratory experiments implicitly constrain participants to make choices and remain in the laboratory for the entire length in order to complete the study. Conversely, (online) field experiments potentially suffer from response bias (attrition). In order to rule out obvious response bias, we compare *Professional* and *Private* for demographic information that we collected in both treatments (further information was only collected in one or the other treatment). We know that the computer-generated randomization worked: about one half, 52.85%, of the 946 clicks on the invitation links in the e-mails were randomly assigned to *Professional* and the remainder to *Private*. Table B.1 shows descriptive statistics for the participants who completed all subsequent stages of our study including the risk task. Compared to the 52.85% who were assigned to *Professional* when they clicked the invitation link in the e-mail, we have 55.27% (262 out of 474) of participants who remained in *Professional* and completed the risk task. The numbers point to slightly greater attrition in *Private* compared to *Professional*.

	Overall	Professional treatment	<i>Private</i> treatment	p-value
	n = 474	n = 262	n = 212	
Mean year born	1972.6	1972.3	1972.9	0.562
Share male	0.59	0.53	0.66	0.003
Share tenured	0.52	0.51	0.54	0.514
Share from Europe	0.79	0.80	0.78	0.607

Table B.1: Descriptive Statistics

Note: Except for mean year born, which is based on a two-sided t-test, p-values are for chi-squared tests.

On average, the participants in the study were born in 1972, meaning that—as of 2016 they were 44 years old on average. Around half of the participants held tenured positions. 19 % live in the US, while 79 % live in Europe. 59 % of the participants are male, the rest is female. Comparing the characteristics across treatments shows that our treatments are balanced, except for gender. The share of males in *Professional* is 53 % compared to 66 % in *Private*. This difference is significant at p < 0.01.

What is the cause of this difference? Fortunately, we have information on the gender distribution in our population (the e-mail list of the scientific organization). We know that about 66.42 % of the members in the population are male. This figure is spot on for the 66 % of males in *Private* (a two-sided binominal probability test does not report a difference, p > 0.99).



Conversely, there are significantly fewer males in *Professional* compared to the expected 66.42 % (two-sided binomial probability test, p < 0.01). In other words, we find the expected share of males in the *Private* treatment while there are significantly fewer males in *Professional* than expected.

Given our design, it was not possible for subjects to actively select themselves *into* any treatment. That is, the smaller amount of males in *Professional* cannot be caused by a selection effect of females into the treatment. It rather seems to be the case that male participants decided to drop out of *Professional* more often than out of *Private* while female participants decided to remain in *Professional* more often. We refrain from speculating about these males' reasons for dropping out as we do not have any demographic information that could shine a light. Given that we do not find any differences for risk-taking of males across treatments, we take this finding with a grain of salt, but remain confident that they do not affect our main results.