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The effect of networks and risk attitudes on the dynamics of migration

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Abstract

Two central concerns for policy makers are the manageability of the rate of migration and the qualities of incoming migrants. This paper addresses these issues by proposing a theory that links risk aversion, the size of expatriate networks, migrant characteristics and the timing of migration. As the size of networks increases over time, finding employment becomes less uncertain, inducing more risk-averse individuals to migrate. Given that recent research suggests a negative relationship between risk aversion, entrepreneurial potential and cognitive ability, the model predicts a decrease in the quality of these 'unobservable' characteristics as networks grow larger. In addition, the dynamic relationship between network size and uncertainty leads to the following hypotheses: when migrants are more reliant on networks for finding work, more individuals will migrate, they will migrate sooner and at a faster rate. I use German Socio-Economic Panel Study (SOEP) data to provide empirical support for the predictions of the theoretical model.

Keywords: migration, risks, network, rate

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Contents

1 Introduction

Two main concerns for policy makers regarding migration are the manageability of the rate of immigration, and the qualities of incoming migrants. The aim of this paper is to shed light on these issues by looking at the underlying mechanisms that could explain how migrant networks develop and how the average characteristics of individuals in these networks change over time. This paper contributes to the economic literature on migration in the following ways: by modelling the link between network size and unobservable characteristics directly, by proposing a new theory of how networks develop over time, and by providing policy-relevant predictions about factors that could influence the rate at which migrant networks are formed.

When looking at labour market outcomes, observable characteristics such as education and work experience explain only around 20–35 per cent of the variation in earnings (Card 1999). This suggests that other characteristics, which often cannot be observed in the data, have a significant impact on wages. Given this unexplained 65–80 per cent, it is no surprise that 'unobservable' characteristics have received a significant amount of attention in the literature (Dostie and Leger 2009; Batista 2008; Rooth and Saarela 2007). In addition, recent research in behavioural economics has identified risk aversion as one of the best proxies for other important 'unobserved' qualities. For example, Dohmen et al. (2010) find that risk aversion is negatively related to cognitive ability, and work by Ekelund et al. (2005) suggests that individuals with lower levels of risk aversion are more likely to become entrepreneurs, holding other factors constant.

These 'unobservable' characteristics are therefore important when looking at the impact of migration on the labour markets of receiving countries. The determinants of whether migrants have above or below average characteristics (relative to the sending-country population) is the central theme of the seminal work of Borjas (1987), and those based on it. The theoretical model in Borjas (1987) makes predictions about the scale and 'quality' of migrants, based on the relative distributions of income and returns to schooling, at home and abroad.

This paper takes an alternative approach to looking at selection on un-observable characteristics, by focusing on another important parameter: mi-grant networks. Migrant networks can influence selection by altering the uncertainty surrounding the migration decision. The idea that uncertainty is an important parameter was first proposed by Sjaastad (1962) and Harris and Todaro (1970) who suggest that migration is an investment decision involving uncertainty. Therefore, only individuals with a certain level of risk aversion will be prepared to migrate when faced with a given combination of migration costs; wage differentials between home and abroad; and the expected probability of finding work upon arrival. I extend this reasoning by allowing migrant networks to influence the uncertainty surrounding the migration decision. More specifically, I assume that networks increase the probability of finding work, therefore reducing the uncertainty faced by future migrants.

Assuming that there is heterogeneity in risk preferences among the sending population, at any given level of uncertainty some will be prepared to move, others will find it too risky, and at the margin there will be individuals who are indifferent regarding staying and migrating. The corresponding level of risk aversion for indifferent individuals is referred to in the model as the cut-off level of risk aversion. I model the cut-off level directly by deriving the Arrow-Pratt measure of absolute risk aversion using migration costs, wage differentials and probability of finding work.[1] Given that networks reduce uncertainty, by improving job prospects for later arrivals, the cut-off level of risk aversion will decrease as networks grow larger. This reduction in the cut-off level will then encourage more individuals (who were previously too risk-averse to migrate) to make the move from the sending to receiving country. As more recent arrivals were not prepared to migrate earlier when uncertainty was greater, they are by definition more risk-averse than previous migrants. The model, therefore, suggests a positive relationship between the size of networks and the average level of risk aversion of individuals in these networks.[2]

The model can be extended to incorporate dynamic aspects of the migration process, by using the mechanism that links networks and uncertainty. A key feature of this extension is that each additional migrant will encourage a different number of individuals to migrate in the next period, if we assume that risk preferences are normally distributed in the sending country. For example, the first migrant will encourage fewer individuals to migrate than a later migrant, even though both reduce uncertainty by the same amount, holding other parameters in the model constant.[3]

While the rate of migration is affected by the distribution of risk preferences, it is also influenced by the extent to which the marginal migrant is able to reduce uncertainty in the receiving country. When there is a heavier reliance on networks for improving the prospects for finding work, each additional migrant will reduce uncertainty by more than if networks were less important. Assuming that risk preferences are normally distributed, the dynamic consequence of a stronger network effect is to increase the rate at which the cut-off level of risk aversion is reduced, compared to when net-works are less important. Using the model outlined above, we simulate this effect and show that when people rely more on networks, more individuals will migrate, they will migrate sooner and at a faster rate. The dynamic element of the migration process has some similarities with the model proposed by Carrington et al. (1996); the three major differences in this paper are that uncertainty is included in the model, the relationship between networks and migration rates is accounted for, and risk preferences are acknowledged as playing an important role in the migration decision.

To conclude the theoretical part of the paper, I look at the relationship between risk aversion and education. By including the network variable in the Roy-Borjas model and assuming that risk aversion and observable characteristics are negatively related, a number

[1] The advantage of using the Arrow-Pratt measure is that it can be calculated directly from the main parameters of migration costs, wage differentials and probability of finding work. This reflects the analogy of migration being like a lottery, with a given sunk cost, a possibility of a pay-out and a corresponding probability of receiving this pay-out.

[2] Recent empirical literature suggests that migrants are indeed more risk-loving than non-migrants regarding internal migration (Jaeger et al. 2010) and international migration (Gibson and McKenzie 2011). I explore this relationship in more detail.

[3] The difference in migration rates between these two periods is caused by the fact that there are more individuals towards the middle of the risk preference distribution than on the left tail of it, assuming that individuals on the left tail of the distribution are extremely risk-loving and individuals on the right tail are extremely risk-averse.

of testable implications can be derived.[4] First, growing networks result in a gradual decrease in the average education level of migrants. Second, growing networks result in a gradual increase in the average level of risk aversion in the migrant population. Third, the rate of migration will increase over time.

The hypotheses derived from the theoretical model could be useful for policy makers in a number of ways. First, if there is a relationship between risk aversion and other important characteristics, earlier migrants will have higher levels of these desirable characteristics than later arrivals. This suggests that policies to attract migrants from a wider range of countries could result in the average migrant having a higher level of unobserved human capital, as the number of individuals of any given nationality will be smaller. Second, the extent to which each arrival can reduce uncertainty for later migrants could also be influenced by policy. For example, integration policies that result in migrants relying less on other network members to find work could reduce both the scale and rate of migration, as suggested by the simulation in this paper.

In order to empirically test the hypotheses that arise from the theoretical model, I use German Socio-Economic Panel Data (SOEP), to look at the relationship between the size of expatriate networks and the level of risk aversion for foreign-born individuals arriving in Germany between 1960 and 2000. The SOEP includes a number of questions designed to capture the risk preference characteristics of respondents and also contains information on a large number of socioeconomic characteristics. When controlling for other determinants of risk attitudes and the year of arrival, I find that there is a statistically significant negative relationship between the size of the network and the willingness of migrants to take risks, as predicted in the model. The magnitude of this effect is significant when compared to other characteristics which traditionally have been shown to determine risk preferences, such as gender and education.

The rest of the paper is organised as follows. Section 2 introduces the model and presents comparative statics, Section 3 develops the model in a dynamic framework, Section 4 provides empirical support for the hypotheses derived from the theory, and Section 5 summarises the main theoretical and empirical findings of the paper, concluding with policy implications.

2 Network size and risk preferences: comparative statics

In this section I show how the cut-off level of risk aversion is derived. This level determines who will migrate and who will stay in the home country in any given time period. Assuming that risk preferences play an important role in the migration decision, this section shows that a lower level of uncertainty will be associated with more risk-averse individuals migrating.[5]

[4] I assume that the initial condition of no networks is characterised by positive selection in education.

[5] Recent theoretical articles have linked risk aversion and migration in a variety of different ways. Heitmueller (2005) links risk aversion of migrants with the choice of destination country, where the countries differ in terms of welfare provision. Wang and Wirjanto (2004) use a stochastic model based on the investment literature to investigate the impact of risk attitudes and uncertainty on the timing of migration decisions. They conclude that in the presence of uncertainty at home and abroad, those with average levels of risk aversion will migrate first.

Instead of interpreting risk preferences as a component of migration costs, I derive the Arrow-Pratt measure of absolute risk aversion explicitly from the costs, benefits and uncertainty facing potential migrants. This allows a link to be made between relative prospects at home and abroad and the characteristics of migrants *vis-a-vis* the source-country population.

I assume that the factors that influence the decision to migrate are: the cost of migration (C), the probability of finding employment (α_t), and the wage differential between home and abroad (B). I assume that all individuals in the source country face the same levels of α_t, C, B in any given period and that C and B do not vary over time. The invariance of B over time relates to the assumption that the marginal migrant does not significantly affect the wage in the host country and a fixed C suggests that the physical costs of migration do not change as the network size increases. I later discuss the consequences of relaxing some of these assumptions.

I propose a two-country model where individuals in the sending country have expected lifetime utility U(W) if they decide not to migrate. I assume this is known with certainty, which is intended to approximate the notion that individuals know a great deal about the job market at home relative to foreign countries and are able to predict their future wealth (if they don't migrate) relatively accurately.[6] The expected lifetime utility of wealth for a migrant is, however, not known with certainty, as there is less available information about the labour market in the receiving country.

The parameters W, B, C, α_t correspond to the conditions involving a gamble, where an individual's risk preference is determined by the acceptance of a lottery with a given cost, pay-off and probability of winning. This combination can be used to determine the Arrow-Pratt measure of absolute risk aversion for the case of migration. In order to calculate the absolute level of risk aversion, I assume that all individuals have the same level of wealth W. Given that wealth W, benefit B, and cost C of migration are invariant, the question of interest is: what level of α_t combined with the other parameters would make an individual indifferent regarding their current level of wealth W (which is known with certainty) and the expected (uncertain) level of wealth from migration? This level of indifference can be written as

$$U(W) = (1-\alpha_t)U(W-C) + \alpha_t U(W+B-C) \tag{1}$$

Individuals have heterogeneous risk preferences, therefore U(W) in (1) will differ between individuals even though W is assumed to be the same for everyone. Assuming a standard, concave, twice differentiable utility function in wealth U(W), the Arrow-Pratt measure of absolute risk aversion can be written as $\rho = -U''(W)/U'(W)$. This implies that the level of risk aversion varies due to the differences in the concavity of individual utility functions.

[6] This assumption is applicable to a pull migration process, where the main motivation to migrate is the prospect of higher wages abroad and not uncertainty in the sending country.

A Taylor expansion can be used to find -U"(W) and U'(W) for(1):

$$U(W) = U(W) + \alpha_t BU'(W) - CU'(W) + U''(W)((1-\alpha_t)C^2 + \alpha_t (B-C)^2)/2$$

The relationship of interest is between the level of uncertainty α_t and the timing of migration decisions. Therefore, holding other factors constant, (while assuming α_t varies over time), the marginal level of absolute risk aversion at time *t* can be written as:

$$\rho^*{}_t = (\alpha_t B - C)/(C^2/2 + \alpha_t B^2/2 - \alpha_t CB) \qquad (2)$$

Where the marginal level of risk aversion ρ_t can be interpreted as a cut-off level of risk aversion at time t. Therefore, the decision rule for individual *i* at time *t* is to migrate, ceteris paribus, when:

$$\rho_i < \rho^*{}_t$$

Where *i* is an individual's level of risk aversion and ρ^*_t is the level of risk aversion of the marginal individual, who is indifferent regarding migrating and staying at time *t* (the cut-off level of risk aversion). Given the formulation of the Arrow-Pratt measure, higher levels of correspond to greater degrees of risk aversion. Therefore, the above inequality states that people in the source country who are less risk-averse than the cut-off level, at time *t*, will migrate at time *t*. Individuals more risk-averse than the cut-off level will stay in the home country.

2.1 Interpretation of migrant networks

There are a number of definitions of migrant networks in the economics literature. However, in the majority of cases networks are seen as being able to influence the costs and risks of future migrants, associated with moving to a new country (Vergalli 2008; Pedersen et al. 2008; McKenzie and Rapoport 2007a; Davis et al. 2002a; Carrington et al. 1996). This effect can be seen either as an individual network effect, where family members and friends back at home are provided with specific help from current migrants (McKenzie and Rapoport 2007b; Boyd 1989), or through increased information flows which reduce the risk of migrating in a less targeted way (Banerjee 1984; Bauer et al. 2002a).

In the theoretical model in this paper the network effect is more closely related to the impact of networks and information flows. The network effect is considered as the marginal effect of the current stock of migrants on the *expected* probability of finding work for future migrants. This marginal effect is evenly distributed among the individuals left in the source-country population. In other words, the expected probability of finding work abroad of all individuals at home, is shifted by the same amount for everyone as a result of migrant networks.

There is evidence to suggest that this information channel plays an important role in the migration decision. Recent work has highlighted the importance of how information flows can reduce the 'cultural distance' between the sending and receiving country and in turn influence the uncertainty surrounding migration decisions (Pedersen et al. 2008). The authors look at country comparisons of migration trends in OECD countries and find that in addition to economic and linguistic factors, previous networks of individuals from the source country are an important determinant of migration flows. This network effect is explained by the importance of acquiring information on policies and institutions in the destination country when it comes to reducing immigration costs. The information flow effect of networks is likely to be significant and increasing due to the development of the internet and other technologies that allow cheap and fast communication and transmission of information.

The expectation of direct help from existing migrants who were not known to individuals before migrating is also incorporated in the theoretical models. Research has shown that in many cultures it is customary for existing migrants to help new arrivals even if they are strangers (Banerjee 1983). In this sense the expected probability of finding work for individuals at home is linked to networks, because of the assumption that help will be provided after migration.

2.2 Networks and migrant self-selection

Network effects can be introduced in Equation 2 if we assume that networks impact on the level of uncertainty α_t in the receiving country, which determines the threshold level ρ_t. It is reasonable to assume that the probability of finding work for a recent migrant depends, to a large extent, on the help she can expect to receive from the expatriate community abroad. This is acknowledged by the literature on network effects, which suggests that networks play an important role in attracting future migrants. The assumptions that a larger network of expatriates in the source country increases the probability of finding work α_t, and that the stock of migrants is increasing over time, lead to the following proposition:

Proposition 1. As the expected probability of finding work in the foreign country increases, the average level of risk aversion in the total migrant population will also increase.

Proof. If there is a positive relationship between α_t and ρ^*_t , the first derivative of ρ^*_t with respect to α_t is:

$$\frac{d\rho_t}{d\alpha_t} = \frac{B(C^2/2 + \alpha_t B^2/2 - \alpha_t CB) - (\alpha_t B - C)(B^2/2 - CB)}{(C^2/2 + \alpha_t B^2/2 - \alpha_t BC)^2}$$

The denominator is non-negative and is equal to 0 only in the specific case when $\alpha_t = 1$ and $B = C$ (see Appendix A). The numerator is positive when:

$$B(C^2/2 + \alpha_t B^2/2 - \alpha_t CB) > (\alpha_t B - C)(B^2/2 - CB)$$

and

$$B > C$$

I assume that the outcome in the foreign country is not known with certainty, therefore $\alpha_t <$ 1. In other words, no individual knows with certainty that they will find work abroad. Furthermore, assuming rational behaviour, even the most risk-loving individual will not migrate if the total cost of migration is equal to or greater than the benefit. Therefore, given that ρ^*_t is bounded by the inequalities (B > C) and $\alpha_t < 0$, ρ_t increases as α_t increases for all possible values. From this, it can be shown that if at least one extra individual migrates in response to a positive shift in ρ_t then the average level of risk aversion will also increase.

If:

$$\alpha_{t=1} < \alpha_{t=2} < \alpha_{t=3} \ldots\ldots < \alpha_{t=i}$$

Then given the restriction B > C:

$$\rho^*{}_{t=1} < \rho^*{}_{t=2} < \rho^*{}_{t=3} \ldots\ldots < \rho^*{}_{t=i}$$

and

$$\frac{\sum \rho^*{}_{t=i}}{n_{t=i}} = \frac{\sum \rho^*{}_{t=(i+1)}}{n_{t=(i+1)}}$$

Where $n_{t=i}$ is the number of individuals in the source country at time t = i.□

The above shows that if network size increases over time, both the probability of finding work and the average level of risk aversion will increase over time as well.

3 Network effects and rates of migration: dynamic simulation

So far the theory has suggested that with growing networks, the aver-age level of risk aversion of migrants will gradually increase. This suggests that there is a difference between early and later migrants.[7] As well as investigating how risk preferences of migrants change over time, the theory outlined above can be used to make predictions about rates of migration. Importantly, the rate of migration will depend on how risk preferences are distributed in the home country. Assuming that risk preferences are normally distributed, I explore how the rate of migration changes as migrant networks in the receiving country increase the probability of finding work.

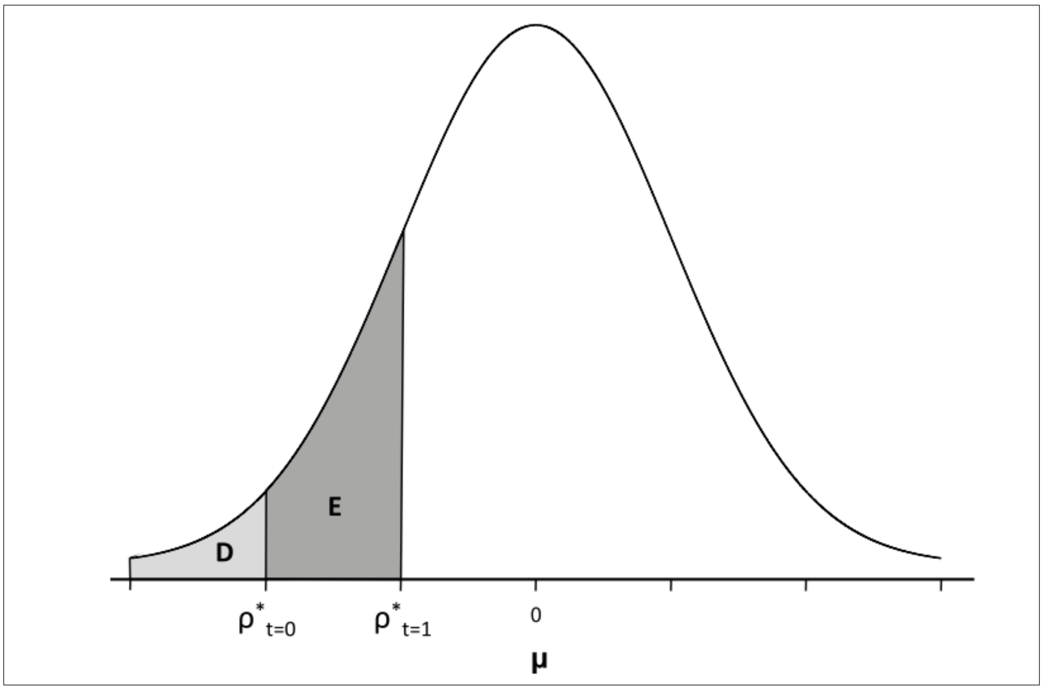
Assuming that risk preferences are normally distributed in the sending country,[8] the proportion of individuals who will migrate at the given levels of W , α_t, C, B is given by the probability that an individual has a lower level of risk aversion than ρ^*_t :

$$P(Z < (\gamma - \sigma_{\rho^*_t}))$$

[7] The difference in characteristics between early 'pioneers' and later followers has been explored in the literature. See for example Bauer et al. (2002b) and de Haas (2010).

[8] Dohmen et al. (2005) find that the responses to the general risk question in the SOEP are approximately normally distributed.

Figure 1: Normally distributed risk preferences



Note: Risk aversion ρt increases, going from left to right. Area D gives the proportion of in order to shift the ρ_t one standard deviation to the right, then the number of people who move between period t = 0 and t = 1 is given by area E. Area E being larger than area D illustrates the fact that even if uncertainty is reduced at a constant rate (one standard deviation per time period) the rate of migration will increase over time. This is true as long as less than half of the population migrates.

This gives the proportion of the source-country population that will migrate, with $\mu\text{-}\sigma_{\rho^*t}$ denoting the threshold level of risk aversion in terms of standard deviations from the mean. Assuming that at the initial time period t=0 the corresponding standard deviation for a normally distributed population is $\mu\text{-}\sigma_{\rho^*t=0}$ the lightly shaded area D in Figure 1 gives the proportion of migrants that migrate at t = 0. If the expected probability of finding work α_t increases in order to shift the ρ^*_t one standard deviation to the right, then the number of people who move between period t = 0 and t = 1 is given by the darker shaded area E. Therefore, the total proportion of the individuals in the receiving country at time t = 1 is given by the combined area of D and E. Figure 1 illustrates that, even when ρ^*_t has a constant rate of increase, the rate of migration will not be constant over time.

Given the shape of the normal distribution curve, the rate of increase will be greater or equal to one, until half of the source-country population has migrated. This is demonstrated by area E being larger than area D. To summarise, Figure 1 shows that: $\rho^*_{t=1} > \rho^*_{t=0}$, D < E and the rate of increase is greater than one when $0 \leq P(Z < z) \leq 0.5$.

3.1 The rate of migration as a function of networks

So far I have assumed that the level of α_t increases over time by exactly the amount required to induce a one standard deviation change in ρ^*_t over that time period. In this section, I look more explicitly at the dynamic interaction of network effects and uncertainty. The two are related because I assume uncertainty is a function of networks in the previous time period and networks are a function of uncertainty in the current time period. The effect of the size of the network is lagged because the impact of an increase in network size due to new arrivals will only affect the migration rate in the next time period. This can be written as:

(3)

In this system of equations M_t is the number of migrants in the source country at time t, and the level of uncertainty α_t is a function of the number of migrants in the source country in the previous time period M_{t-1}. The number of migrants in the source country at any given time is a function of costs, benefits, marginal risk aversion and uncertainty. Given that migration costs and benefits are fixed, it is the changing level of uncertainty α_t, governed by network effects that drives the migration process.

Equation 3 can be written as a dynamic system of equations, where the proportion of individuals in the receiving country at time *t* is determined by the threshold level of risk aversion ρ_t and is given by the following cumulative distribution:

$$M_t = \phi(Z_{\rho^*_t}) \tag{4}$$

Where ϕ ($Z\rho^*_t$) is the standard normal density function. Z_{ρ^*t} is the standard deviation of the threshold level of risk aversion, relative to the mean level of risk in the sending country, and can be written as:

$$Z_{\rho^*_t} = \frac{\rho^*_t - \bar{\rho}}{\sigma_\rho}$$

$\bar{\rho}$ is the mean level of risk aversion in the sending country and σ_ρ denotes one standard deviation. Given that these two population parameters are fixed, the stock of migrants at time t is determined by the threshold level of risk aversion. This, in turn, is determined by the threshold level condition, as derived in section 2:

$$\rho^*_t < (\alpha_t B - C)/(C^2/2 + \alpha_t B^2/2 - \alpha_t CB) \tag{5}$$

As discussed above, the parameters B and C are constant over time; therefore, changes of the threshold level ρ^*_t are governed by α_t, the probability of finding work in the receiving country. In turn, this probability is affected by the size of networks, and can be expressed as:

$$\alpha_t = \frac{\underline{\alpha} + M_{t-1}X}{2} \tag{6}$$

where $M_{t-1}X/2$ is the network effect of α_t, and $M_{t-1}X$ takes a value between 0 and 1. This is split into two components. The first component M_{t-1}, is the size of the network, lagged by one time period: I call this the 'Network Scale Effect' as it is the effect that the size of the network has on the probability of finding work for new arrivals. The second component X is the marginal effect of M_{t-1} on α_t. I call this the 'Network Impact Effect', because it tells us the extent to which each migrant can increase the probability of finding work for new arrival.

Even with no networks in the receiving country, I assume that there is a certain level of uncertainty, which is given by $\underline{\alpha}/2$, which has a value between 0 and 1 and gives the level of α_t at time t = 0. This gives the probability of finding work even if there are no migrants in the receiving country.[9]

The dynamic process is set in motion by the initial level of uncertainty $\underline{\alpha}/2$ (Equation 6), which results in a specific threshold level ρ^*_t (Equation 5) that leads to all individuals that are more risk-loving than the threshold to migrate and make up the stock of migrants at time t given by M_t (Equation 4). In the next time period the level of uncertainty will be determined by the network in the previous time period M_{t-1}, which brings us back to Equation 6.

3.2 Strong and weak network effects

So far I have assumed that the Network Impact Effect (X) is a predetermined value. However, it could well be the case that in some migration processes each migrant can reduce uncertainty by a great deal while in other cases the marginal effect is small. In order to see how changing the strength of this effect impacts on the dynamics of migration, I simulate the migration process using Equations 4 to 6, first with a low and then a high value for *X*. The results are displayed in Figure 2 and show the changing proportion of migrants living in the receiving country over a given time period. In Figure 2, the solid line denotes strong network effects and the broken line shows the outcome when Network Impact Effects are less important (X is larger in the former than in the latter). The results of the simulation show that network effects alter the timing and rate of migration.

As well as demonstrating that stronger networks increase the total stock of migrants, Figure 2 also shows that: first, individuals migrate sooner when network effects are stronger; and second, the rate of migration is faster. The former is demonstrated by the fact that the solid line is to the right of the broken line and the latter by the fact that the slope of the solid line is greater than that of the broken line. This shows that when potential migrants rely heavily on networks to find work, it could lead to a faster rate of migration.

This hypothesis is a central contribution of this paper as it suggests that integration policies that reduce the reliance of migrants on networks could not only increase the average 'quality' of migrants but also reduce the rate and scale of migration, holding other factors fixed.

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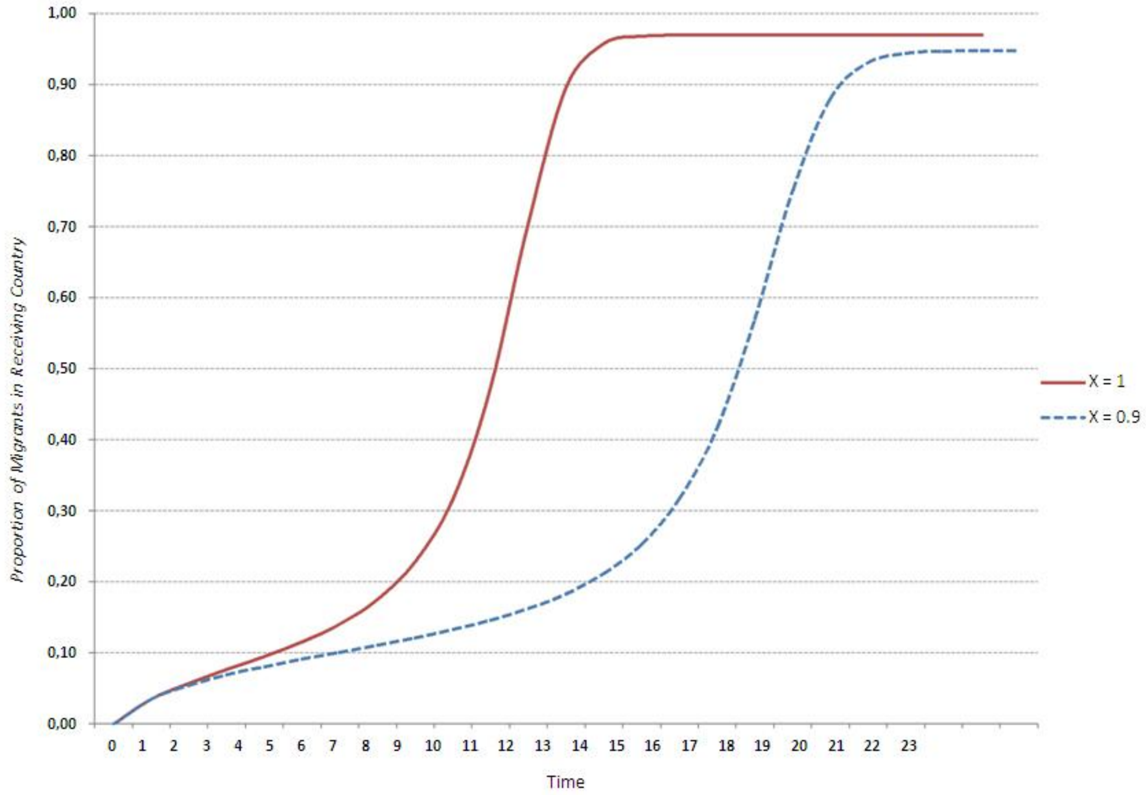
[9] $\underline{\alpha}$ plays two important roles. First, it provides the initial condition for the first iteration of the simulation, and second it ensures that some individuals in the sending country will never migrate irrespective of the strength of the network effect. For example, if $\underline{\alpha}$ has a low value, even if $M_{t-1}X$ is tending to 1, there will be a proportion of individuals in the source country who will never migrate.

Figure 2: Migration dynamics with strong and weak network effects



Note: The figure above shows the proportion of individuals that migrate in each time period, with strong (solid line) and weak (dashed line) network effects. In the initial time period there are no migrants in the receiving country ($M_{t=0}$ = 0). The level of uncertainty with no networks is assumed to be ($\alpha_t 2$ = 0.4); the wage differential is (B = 180); cost of migration is (C = 50); the mean Arrow-Pratt level of absolute risk aversion in the sending country is (μ= 0. 01); and the risk attitudes are normally distributed with a standard deviation of (σ = 0.002). For the solid line the individual network effect is X = 1, and for the dashed line it is X = 0:9. The figure shows that when migrants are more reliant on networks (stronger individual network effect), more individuals will migrate, they will migrate sooner and at a faster rate.

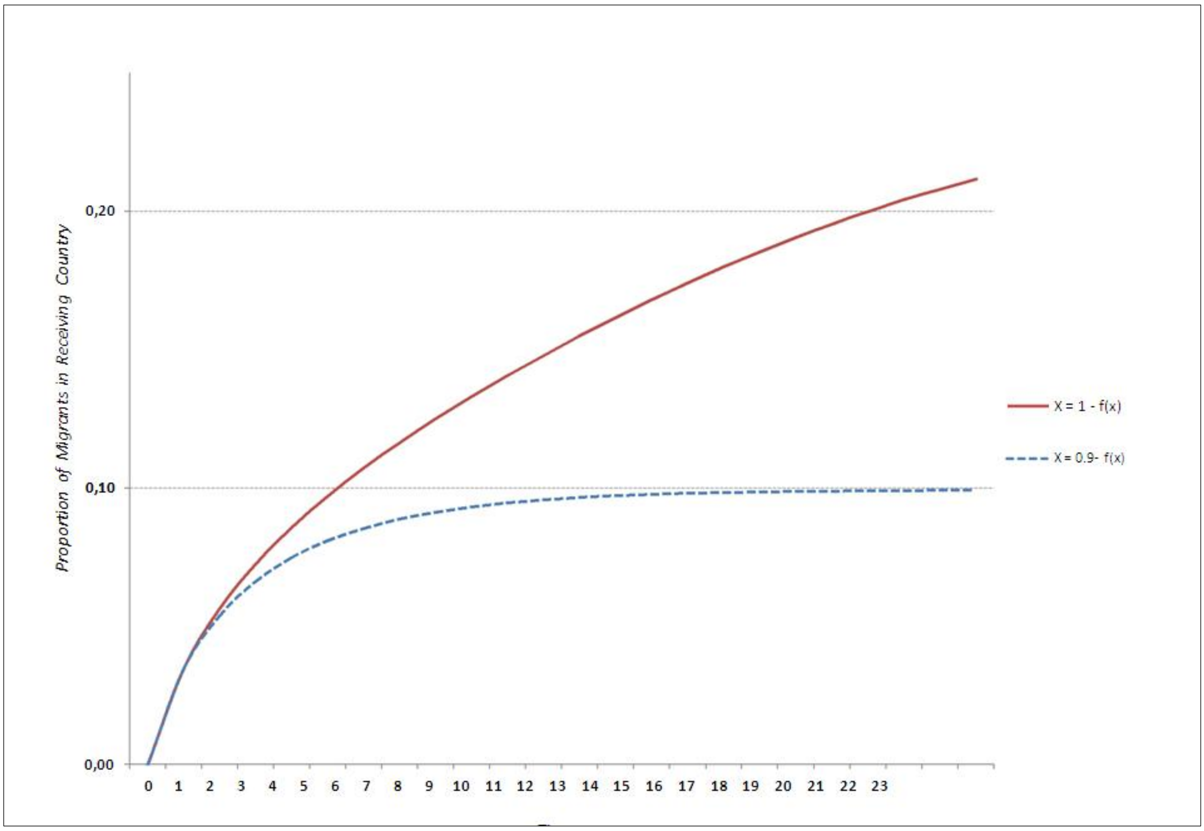
3.3 Decreasing marginal network effect

So far I have assumed that each individual decreases uncertainty by the same amount, irrespective if the already existing size of the network. It could be conceivable that the marginal network effect diminishes as networks grow. This diminishing influence of networks has been modelled theoretically by Vergalli (2008) and Bauer et al. (2002b), and has been found empirically in articles such as Davis et al. (2002b). Many studies in the literature suggest that the network effect has an 'inverse U' shape related to the size of the network.

I incorporate the insight that the marginal effect of migration could be diminishing, by making marginal individual network effects a negative function of network size. More specifically, I assume that there are a limited number of jobs for potential migrants in the host country and that the positive impact of having more individuals in the receiving country from the source country is counterbalanced by fewer available jobs in the source country. Figure 3 shows a simulation where a 1 percentage point increase in network size reduced the individual network effect by 1 per cent. This decreasing marginal network effect is modelled for a higher (solid line) and a lower (dashed line) initial network strength.

Comparing Figure 3 to Figure 2, it is clear that fewer individuals will migrate and at a lower rate, when marginal network effects are decreasing. However, when comparing strong and weak initial networks, when both have decreasing marginal network effects (as in Figure 3), the main conclusions outlined above remain. When initial network effects are stronger, more individuals will migrate at an earlier time and at a faster rate.

Figure 3: Migration dynamics with declining network effects



Note: As in Figure 2, ($M_{t=0}$ = 0), ($\alpha/2$ = 0.4), (B = 180), (C = 50), (μ= 0; 01), and (σ=0.002). Different from Figure 2, individual network effects diminish as networks grow. For the solid line the individual network effect for the first migrant is X = 1, this effect is reduced by 1% for every 1% increase in the migrant population, and for the dashed line the network effect for the first individual is X = 0.9 and this effect is also reduced at the same rate. The figure shows that modelling individual network effects as decreasing reduces the total number of migrants when compared to fixed network effects. However, comparing strong and weak initial network effects leads to the same conclusion as the initial model. When initial networks are stronger individuals will migrate sooner and at a faster rate.

3.4 Risk attitudes and observable characteristics

further way to extend the model is to consider the relationship between the selection of migrants based on risk preferences and other characteristics, such as education. While the model so far has focused specifically on risk preferences, the insights of the Roy-Borjas model can provide predictions on selection in terms of other characteristics. While the theory set out above suggests that the average level of risk aversion increases in the migrant population if networks are growing, whether this migrant group is positively or negatively selected in terms of observable characteristics could be determined by the parameters of the Roy-Borjas model (Borjas 1987). In this case, while the traditional Roy-Borjas framework predicts initial selection in terms of observable characteristics, we can predict how the 'quality' of migrants in terms of these characteristics changes as networks grow. These predictions can be made if we know the correlation between those characteristics and risk preferences. I focus here on education, but the same reasoning can be applied to other observable characteristics.

Starting with the initial condition of no networks, migrants will either be positively or negatively selected in terms of education (compared to the source-country population) based on whether education is rewarded more highly at home or abroad (Borjas 1987). Therefore, only individuals with a certain level of education will find it advantageous to migrate, either because their high education could command a higher income abroad (positive selection) or because wages for individuals with low education are compensated abroad due to redistribution policies (negative selection).[10]

Taking the case of positive selection in education, the value B in Equation 1 would only be sufficiently high for individuals on the right tail of the education distribution, i.e. individuals earning above the average income level. If we relax the assumption that everyone has the same education (and in-come) in Equation 1, then selection in terms of risk preferences will depend on the correlation between education and risk attitudes. If we assume that education and the willingness to take risks are positively correlated, then the first migrants will be positively selected both in terms of education and willingness to take risks. As networks increase and uncertainty is reduced, individuals with a combination of lower education and lower willingness to take risks will now migrate. A marginal reduction in uncertainty will increase the number of individuals willing to migrate, both because more individuals have a marginally lower level of education than the initial condition and more individuals are marginally more risk-averse.[11] Alternatively we can say that the joint probability of migrants being marginally more risk-averse and having a marginally lower level of education increases as networks in-crease and uncertainty is reduced. In the case of negative selection, the result of a decrease in uncertainty is less conclusive and depends on the strength of the correlation between risk preferences and education.

These insights can be incorporated more formally in the framework of the Roy-Borjas model by interpreting risk attitudes as the variant component of migration costs, where these costs are normally distributed in the source-country population. This approach follows the insight provided by Chiquiar and Hanson (2005) and is explicated in Appendix B.

[10] In terms of the model in this paper, the parameter B (benefit of migration) in Equation 1, could be interpreted as this advantage to migration.

[11] Given that the initial threshold income level is on the right-hand side of the income distribution, a marginal shift to the left will increase the number of people willing to migrate.

4 Empirical analysis of the link between network size and risk preferences

This section proposes to examine the central hypothesis provided by the theoretical model, that when migrant networks are larger, the average migrant will be more risk-averse.

4.1 Econometric model

The predictions of the theory are based on a two-country model, where the risk attitudes of individuals are relative to the source-country population. In reality, migrant communities in the source country often represent a number of nationalities. One would expect the risk preferences between these nationalities to differ because of cultural reasons. Therefore, when looking at migrants from a variety of source countries it is important to account for country-specific differences in risk attitudes. To control for these differences, I use a country of birth fixed effects model to identify the relationship between network size and willingness to take risks.

I investigate the impact of network size on risk attitudes after controlling for individual determinants of risk attitudes (as found in the literature), the year of immigration and unobserved heterogeneity due to cultural differences between nationalities. The following equation forms the empirical framework of the analysis:

$$Risk_{ij} = \beta_1 Net_{ji} + \beta_2 Myear_i + \beta_3 \boldsymbol{X_i} + \alpha_j + \varepsilon_i$$

where $Risk_{ij}$ is a measure of the willingness of individual i who migrated from country j to take risks. Net_{ji} is the number of foreign-born individuals from country j in the receiving country one year before individual i migrates.[12] $Myear_i$ is the year individual i migrated to the receiving country. $\boldsymbol{X_i}$ is a vector of individual characteristics which have been shown to affect risk attitudes such as age, gender, height, income, self-employment, and schooling. α_j is the country of birth fixed effect to account for cultural differences in risk attitudes and ε_i is the error term.

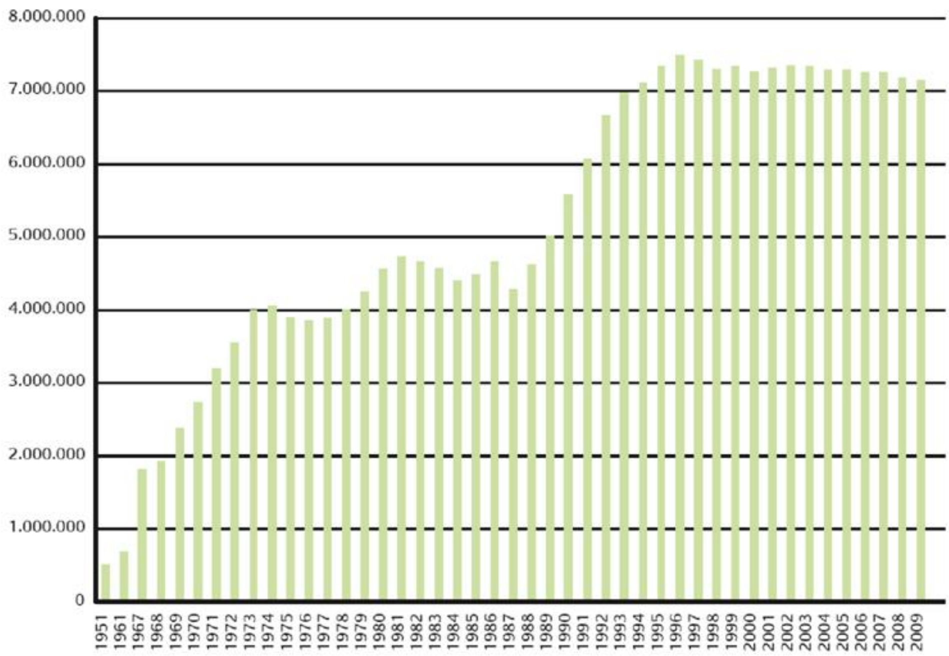
4.2 Data description

I use the German Socio-Economic Panel Study (SOEP) which is a representative panel survey of the resident population of Germany, conducted since 1984. Germany is a relevant country to test the impact of migrant networks as the number of foreign-born individuals increased dramatically between 1951 and 2000 (see Figure 4), the period used in this paper. While Turkey, Italy, Former-Yugoslavia, Poland and Greece are the source countries for the majority of individuals in the data-set, a large variety of countries are represented (see Table 4 in Appendix B). The variable for the size of the expatriate network between 1951 and 2000 is estimated from a combination of sources.[13]

[12] It is lagged by one year to account for the fact that the migration decision is made one year before migration.

[13] I use two main sources to estimate the actual size of the migrant population for the countries and years

Figure 4: Stock of migrants in Germany, 1951–2009



Source: Immigrant Figures, National Department for Migration and Asylum
(Ausländerzahlen 2009. Bundesamt für Migration and Flüchtlinge)

As well as having a large sub-sample of migrants, the SOEP also includes a module on risk attitudes which includes questions that gauge the willingness of individuals to take risks. These questions were included in the study after 2004 and include self-evaluation of an individual's 'willingness to take risks, in general'; along with measures of risk preferences in other domains. I use the general self-assessed risk measure, as it has been shown to be the best predictor of an individual's actual general risk-taking behaviour.[14] The general measure of risk aversion was found to be an especially good predictor for the measure involving real money incentives and therefore suggests that this measure is valid for the domain of risk preferences in the domain of money.

While it has been shown that risk attitudes vary between different domains, the theoretical model being tested in this paper loos at risk in the money domain, equivalent to a risky investment decision, which is the domain of risk that the question was designed to capture. The possibility of specific strategies, by some individuals, involving gambling on smaller stakes that are not translated to a larger financial decision, such as migration, cannot be ruled out. Nevertheless, the SOEP measures of risk have been tested using real incentives and capture risk preferences well compared to measures used in other data sets.

represented in the data-set; the German Statistical Office, and World Bank International Migrant Stock data. The network size variable is expressed in units of 10,000 migrants.

[14] Dohmen et al. (2005) tested the behavioural relevance of the survey measures by conducting a complementary field experiment on a representative sample of 450 individuals involving real significant monetary pay-offs. They found that the general risk question was the best performing question for predicting real outcomes of risk attitudes.

In order to test the relationship between network size and risk aversion, the sample contains foreign-born individuals who entered Germany after 1960 and before 2000, and who answered at least one of the questions regarding personal willingness to take risks that were included in the SOEP surveys between 2004 and 2009. Looking first at descriptive statistics suggest that there is a negative relationship between network size and willingness to take risks, with a correlation of -0.1374 (Spearman; p < 0:00001) before controlling for other factors.

4.3 Empirical results

In order to test the theoretical model outlined above, I compare the risk attitudes of individuals who arrive when networks are small, to risk attitudes of migrants who arrive when networks are large. I control for the main characteristics that have been shown to be important determinants of risk preferences in the literature (Jaeger et al. 2010; Dohmen et al. 2010; Bonin et al. 2009, 2007; Ekelund et al. 2005; Cramer et al. 2002). The independent variable is the size of the migrant network one year before migrating.

Regressions 1 to 4, in Table 1 in Appendix B, show the results for OLS regressions. The first specification includes the characteristics that are most often used as explanatory variables in the empirical risk literature, and provides a comparison between this paper and existing research to ensure the validity of the control variables. The R squared and the signs of the coefficients are similar to those reported in the studies mentioned above. For example, older individuals, women, and individuals with no schooling are expected to be less risk-loving; whereas taller, wealthier and self-employed individuals are expected to be more risk-loving. This confirms that the variables used in the specification are valid controls for the sample used.

Regression 2, in Table 1, includes the dependent network variable with age, gender and height controls. These are individual characteristics that have very limited measurement error and are unlikely to suffer from reverse causality. In this specification, the network variable is negative and significant. Including other individual controls of wages, self-employment and schooling reduces the magnitude of the effect but does not change the sign or its statistical significance. Finally, Regression 4 includes the control for 'immigration year', which captures the time a migrant has spent in Germany. Controlling for the year of arrival does not significantly change the magnitude or the sign of the coefficient, and it remains significant at the 1 per cent level. The OLS specification provides support for the hypothesis that network size and willingness to take risks are negatively related.

Given that an important source of variation in risk attitudes could be due to nationality, I control for these unobserved characteristics by using a country of origin fixed effect in Regressions 5 to 7, in Table 1. Regression 5 includes the basic characteristics as in Regression 2, and shows that the network variable still has a negative sign and is highly significant. Including the other individual level characteristics of wages, self-employment and schooling, shown in Regression 6, marginally increases the magnitude of the point estimate, and the variable remains negative and statistically significant. Controlling for years of immigration in the fixed effects specification does not significantly alter the magnitude of the network estimate but it does lose its insignificance. This could potentially be due to high correlation between year of arrival and network size when focusing on within-country variation, as most countries experienced growing networks. The estimate does, however, suggest that the relationship between network size and risk aversion could be negative even when year of arrival is controlled for.

Looking at the results of the fixed effects regressions suggests that the point estimate on the network variable is approximately -.05. The interpretation of this result is that an increase in the network size by 10,000 individuals in Germany reduces the average willingness to take risks by 0.05 points on the risk measure scale. While this might appear to be a small magnitude, when considering the rate of migration in Germany this becomes significant. For example, the number of Turkish-born individuals increased by around 918,300 between 1965 and 1975; this would suggest a decrease in the willingness to take risks by just under 5 points on the risk scale for this period. This is similar to the magnitude of the difference between being male and female (6.7) or the effect of completing secondary school (5.0).

While the stock of migrants increased in Germany for most nationalities, this was not the case for all countries over the whole time period in question.

To ensure that these observations are not driving the results, I restrict the sample only to time periods and countries that saw an increase in the number of migrants. Table 2 shows the results when observations are restricted to individuals who arrived at a time when migrant networks were increasing. Regressions 1 to 4 in Table 2 show that that an increase in the network size by 10,000 individuals in Germany reduces the average willingness to take risks by between 0.03 and 0.05 points on the risk measure scale, depending on the control variables used. These results are comparable to the full sample presented in Table 1, with the magnitude of the effects being marginally lower, and the result remaining significant at the 5 per cent level for specification 1 to 3 and 6 per cent for specification 4. Finally, Regression 5 controls for the year of migration. As in the case of the full sample the point estimate remains negative and the magnitude increases relative to the other specification, while losing its significance. The results presented in Table 2 suggest that the results are not being driven by periods when networks are decreasing in size. As before, the magnitude of the effects is significant in the context of the scale of migration experienced in Germany over the years in the sample.

4.4 Alternative explanations

The empirical results show that there is a correlation between network size at time of arrival and willingness to take risks, while controlling for other individual characteristics and the year of migration. Given that the self-assessed risk measure was recorded between 2004 and 2009, an alternative explanation for the results could be that migrants assimilated to the native level of risk aversion by becoming more risk-loving over time. Indeed, descriptive statistics suggest that native-born Germans are in fact more risk-loving than most of the migrant groups.[15] Table 5 in Appendix B shows a comparison of the average share of native-

[15] This highlights the importance of cultural differences and the comparison of migrants and non migrants from a given country or cultural background rather than comparing migrants and non migrants in general. When migrants and non-migrants from the same country are compared (McKenzie and Rapoport 2007a), we find that migrants are indeed more risk-loving than non migrants.

born individuals and those born outside Germany. The figures show that in the case of the three most popular sending countries in the sample, and for the average of the rest of the migrants, native Germans are more risk-loving.

It is possible to explore this alternative explanation of assimilation further as the SOEP data-set contains repeated risk measures for migrants, recorded in 2004 and 2009. If the assimilation hypothesis were true one would expect migrants to become more risk-loving over these five years. However, after controlling for age effects the data suggest that there was a marginal decrease in the willingness of migrants to take risks in these five years. As shown in Table 6 in Appendix B, on average a migrant became 4 points less risk-loving on the risk measure scale between 2004 and 2009. In fact, there was a decrease in the willingness to take risks in all of the relevant risk domains measured in the survey, as shown in Table 6. This evidence that migrants are becoming more risk-averse over time gives weight to the hypothesis that the negative sign on the network variable in Tables 1 and 2 is not driven entirely by assimilation effects.

4.5 Empirical results conclusion

Using SOEP data I provide some evidence to support the theory that there is a link between the size of networks and the average level of risk aversion of migrants. In all of my specifications I find that individuals who arrived when networks were larger are on average expected to be less risk-loving. This effect is statistically significant and of a considerable magnitude compared to traditional explanatory variables used to explain risk-taking behaviour.

There are real difficulties in testing the theoretical model empirically, related to the availability of data-sets that contain both detailed information on migration as well as risk preferences. The SOEP data-set is a one of a very few data-sets which does. The migrants' sub-sample of the data-set, however, contains mainly guest-workers who arrived before 1990, which limits the ex-tent to which these results can be generalised to other migration processes. However, the empirical analysis provides a first step to understanding the relationship between risk preferences and the dynamics of international migration, which can be built upon when more detailed data containing both migrants and risk preferences become available.

5 Conclusion

As the total number of migrants continues to rise globally, policy makers in source countries are becoming increasingly concerned about the rate of migration as well as the level of human capital of recent arrivals. This paper develops a theoretical model to investigate how the average risk attitudes of migrants changes with the size of networks and how networks can influence the rate of migration. The assumption that networks reduce un-certainty surrounding the migration decision results in the conclusion that larger networks are associated with a higher average level of risk aversion. Furthermore, assuming that risk preferences are normally distributed in the source country, the link between network size and uncertainty leads to the following testable hypotheses: when networks effects are stronger, more individuals will migrate, they will migrate sooner, and at a faster rate.

The first result suggests that over time the average migrant will be more risk-averse. Assuming that risk aversion is negatively related to other desirable characteristics such as entrepreneurial potential and cognitive ability, growing networks will have implications for the average human capital in both the sending and receiving country.[16] There will, therefore, be a negative effect over time for the receiving country and a positive effect for the sending country, in terms of unobservable human capital. A specific policy recommendation for the receiving country leading on from this conclusion is that a larger number of small migrant networks could result in higher levels of human capital, holding other factors fixed. This suggests that a migration policy encouraging diversity could have positive effects.

In terms of migration rates, the results of the simulations suggest that when networks are more important, migrants move sooner and within a shorter period of time. This has relevance for the source country where an unexpected surge in migration could result in shortages of public services, such as housing and welfare. For the sending country, stronger networks suggest a faster 'drain' of human capital. Understanding this relationship could help governments to plan for such instances and devise strategies to avert labour shortages in the sending country and strains on public resources in the receiving country.

The framework is extended to investigate the relationship between selection based on risk attitudes and selection based on other observable characteristics, such as education. Under a given set of assumptions, it is shown that in the case of positive selection in education, early migrants will be positively selected in terms of both education and risk preferences, with the selection becoming less positive in both characteristics as network size increases. This leads to the conclusion that as networks grow, the human capital of migrants in terms of both observable and unobservable characteristics will decrease, while the rate of migration will increase.

The link between migrant networks and risk preferences is tested empirically using German Socio-Economic Panel Data. I find that after controlling for other determinants of risk attitudes, and the year of arrival, there is a statistically significant negative relationship between the size of the network and the willingness of migrants to take risks, as predicted in the model. The magnitude of this effect is significant when compared to other characteristics which traditionally have been shown to determine risk preferences, such as gender and education.

[16] The link between risk aversion and entrepreneurial talent is explored in Kanbur (1979), Ekelund et al. (2005) and Bonin et al. (2007).

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Appendix A

Find the solution for α ; B; C when:

$$C^2/2+\alpha_t B^2/2-\alpha_t BC=0$$

given the constraints:

$$B \geq C$$
$$\alpha \leq 1$$
$$(B, C, A) \geq 0$$

Rearranging gives:

$$\frac{C^2}{2BC-B^2}=\alpha$$

Combining gives:

$$\frac{C^2}{2BC-B^2} \leq 1$$

Given the constraints gives the unique solution:

$$B=C, \alpha=1$$

Appendix B

This appendix is based on the Chiquiar and Hanson (2005) interpretation of the Roy-Borjas model and follows the same notation for clarity. The wage distribution for individuals in the home country is given by:

$$\ln(w_i) = \mu_i + \delta_i s + \varepsilon_i \qquad \text{(Appendix B.1)}$$

where i = 0 is the wage distribution in the home country and i = 1 is the wage distribution of migrants in the receiving country. w_i is the wage in country i, μ_i is the zero-schooling mean wage in i, δ_i is the return to schooling in i, s is the level of schooling, and ε_i captures deviations from mean earnings and is normally distributed. ε_0 and ε_1 have correlation coefficient ρ_{10}> 0. Schooling is a random variable with distribution:

$$s = \mu_s + \varepsilon_s \qquad \text{(Appendix B.2)}$$

where μ_s is mean schooling and ε_s is normally distributed.

Combining B1 and B2, an individual will migrate if:

$$\ln\left(\frac{w_1}{w_0 + C}\right) \approx (\mu_1 - \mu_0 - \pi) + \mu_s(\delta_1 - \delta_0) + (\varepsilon_1 - \varepsilon_0) + \varepsilon_s(\delta_1 - \delta_0) > 0 \qquad \text{(Appendix B.3)}$$

where C is migration costs and π= C/w_0 is time-equivalent migration costs. In the context of the model in this paper, variation in depends on the risk preference of the individual, with more risk-loving individuals facing lower migration costs. This reinterpretation of π allows for heterogeneity in risk preferences to be incorporated into the Roy-Borjas model without major adjustments. This parameter has the distribution:

$$\pi = \gamma_\pi + \varepsilon_\pi \qquad \text{(Appendix B.4)}$$

where is the mean migration cost, or in other words the migration cost for the individual with mean risk characteristics; ε~N(0; δ^2_π). The correlation coefficient for ε_π and ε_i is $\rho_{i\pi}$, where i = 0, 1, s. Therefore the probability that an individual migrates to the United States is given by:

$$\Pr(v > -[\gamma_1 - \gamma_0 - \gamma_\pi + \gamma_s(\delta_1 - \delta_0)]) = 1 - \phi(z) \qquad \text{(Appendix B.5)}$$

where Φ(z) is the standard normal distribution function, v = (ε_1-ε_0- ε_π) and z = -[$\mu_1 - \mu_0 - \mu_\pi$ +$\mu_s(\delta_1$-δ_s)]/σ_v. This probability gives the rate of migration. Whether individuals will be positively or negatively selected can be determined by using the information in (B1-B5). Letting v' = v/σ the expected level of schooling for a migrant is:

$$E(s \mid v' > z) = \mu_s + E(\varepsilon_s \mid v' > z) = \mu_s + \left(\frac{\sigma_s^2}{\sigma_v}(\delta_1 - \delta_0) - \frac{\sigma_\pi \sigma_s}{\sigma_v}\rho_{s\pi} \right)\lambda(z) \qquad \text{(Appendix B.6)}$$

where λ denotes the inverse Mills ratio $\phi(z)/[1-\Phi(z)]$, and $\Phi(z)$ is the standard normal density function. Migrants will have above average education levels relative to the home population if the term in brackets in (B6) is positive. Conversely, migrants will have below average education levels relative to the home population if the term in brackets is negative. Assuming that returns to schooling are larger in the receiving than the sending country $(\delta_1 - \delta_0) < 0$, migrants will have below average to average schooling if $\rho_{s\pi}$ is not too negative and above average schooling if $\rho_{s\pi}$ is negative and large in absolute value relative to $\delta_1 - \delta_0$. While it is not possible to know the relative magnitude of $\rho_{s\pi}$, there is significant empirical evidence that more educated individuals are more risk-loving (Cramer et al. 2002; Dohmen et al. 2010; Ekelund et al. 2005; Halek and Eisenhauer 2001; Hartog et al. 2002). Therefore, it is reasonable to assume that $\rho_{s\pi}$ will be negative, and more educated individuals face a relatively lower 'cost' when faced with a high level of uncertainty. Following the conclusions of Chiquiar and Hanson (2005), it is clear from (B6) that positive selection in terms of education is more likely the stronger the negative correlation between observable skills and migration costs. In terms of the framework above, positive selection is more likely the higher the positive correlation between education and the willingness to take risks.

The Roy-Borjas framework can also say something about changing levels of uncertainty and the scale of migration. If there is positive selection, a higher value of $\lambda(z)$ will make the second term in (B6) more positive, meaning that selection will be more positive, and the average migrant will be more educated as a result of the shift. Conversely, a lower value of $\lambda(z)$ will make the term in brackets less positive, meaning that selection will be less positive, and the average migrant will be less educated as a result of the shift. If we assume that the average level of uncertainty is reduced over time and μ_π is decreasing, from A5 we can see that the scale of migration will also increase, and the inverse Mills ratio $\lambda(z)$ will decrease. If there is positive selection, a decreasing value of $\lambda(z)$ (increasing number of migrants) will mean that selection in terms of education will become less positive and the average migrant will be less educated. Furthermore, given that the initial selection in terms of risk aversion and education occurs from the positive tail of the distribution, a marginal shift to the left will result in an increase in the number of migrants, as the joint probability of having a lower level of education and lower willingness to take risks increases.

If we assume that initially individuals are negatively selected in terms of education, the outcome is more ambiguous, as selection in terms of education will become more positive and selection in terms of willingness to take risks will become more negative. Whether the rate of migration will increase or not will depend on the relative importance of the risk aversion and the education parameter with respect to changes in uncertainty.

The same approach can be applied to look at income in the framework of the Roy-Borjas model. If it is assumed that income is also positively related to the willingness to take risks, as is suggested by the literature, then the conclusions are identical to the case of education.

Table 1: Risk attitudes and networks, OLS and FE Comparison. DV: Willingness to Take Risks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	OLS	FE	FE	FE
Network(t-1)		-0.074	-0.045	-0.046	-0.044	-0.049	-0.055
		(0.006)	(0.009)	(0.009)	(0.016)	(0.020)	(0.038)
Age	-0.374	-0.611	-0.498	-0.508	-0.587	-0.503	-0.501
	(0.062)	(0.091)	(0.101)	(0.118)	(0.093)	(0.116)	(0.122)
Female	-3.697	-7.589	-4.846	-4.763	-9.475	-6.387	-6.367
	(1.426)	(2.185)	(2.378)	(2.277)	(2.092)	(2.029)	(2.098)
Height	0.291	0.363	0.240	0.247	0.249	0.167	0.167
	(0.097)	(0.102)	(0.141)	(0.134)	(0.092)	(0.124)	(0.124)
Wages	2.083		2.554	2.545		2.340	2.350
	(0.783)		(1.116)	(1.102)		(1.201)	(1.177)
Self Employed	2.971		3.329	3.336		3.388	3.385
	(0.447)		(0.710)	(0.705)		(0.801)	(0.793)
No School	-7.650		-5.047	-5.119		-5.517	-5.533
	(1.580)		(2.207)	(2.087)		(2.393)	(2.476)
Migration Year				-0.046			0.035
				(0.097)			(0.260)
Constant	15.705	21.031	34.031	125.413	40.418	49.529	-20.175
	(18.369)	(22.677)	(29.172)	(205.166)	(20.012)	(26.738)	(522.674)
Observations	1615	1289	846	846	1289	846	846
R-sq	0.166	0.190	0.206	0.206	0.153	0.187	0.187
Within R-sq					0.153	0.187	0.187
Between R-sq					0.266	0.145	0.147

Standard errors in parentheses
p < 0:05,   p < 0:01,   p < 0:001

Note: Wages are expressed in EUR 1000's, 'No School' is a dummy variable for not completing secondary education, dependent variable is a measure of 'general willingness to take risks' on a 0–100 scale, 'Network(t-1)' is the size of the expatriate network one year before an individual migrates, expressed in 10,000 units. The first four columns show OLS specification and columns 5 to 7 show Fixed Effects regressions.

Table 2: Risk attitudes and networks, increasing networks only. DV: Willingness to Take Risks

	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Network(t-1)	-0.032	-0.034	-0.047	-0.040	-0.055
	(0.015)	(0.015)	(0.022)	(0.021)	(0.049)
Age	-0.568	-0.550	-0.556	-0.487	-0.483
	(0.098)	(0.078)	(0.111)	(0.116)	(0.118)
Female	-9.159	-7.179	-6.756	-6.702	-6.665
	(2.482)	(1.636)	(2.111)	(1.986)	(2.035)
Height	0.286	0.228	0.228	0.191	0.189
	(0.096)	(0.090)	(0.135)	(0.129)	(0.129)
Wages		2.940	2.270	2.040	2.065
		(1.015)	(1.298)	(1.228)	(1.209)
Self Employed			2.926	3.067	3.057
			(0.875)	(0.851)	(0.837)
No School				-5.815	-5.847
				(2.258)	(2.303)
Migration Year					0.090
					(0.308)
Constant	32.232	34.429	41.200	44.687	-133.955
	(20.755)	(18.531)	(28.711)	(27.831)	(610.487)
Observations	1096	1020	764	716	716
Overall R-sq	0.186	0.208	0.210	0.197	0.194
Within R-sq	0.161	0.183	0.192	0.184	0.184
Between R-sq	0.246	0.248	0.165	0.141	0.148
Number of Countries	49.000	48.000	43.000	41.000	41.000
Average Size of Group	22.367	21.250	17.767	17.463	17.463

Standard errors in parentheses
p < 0:05, p < 0:01, p < 0:001

Note: Wages are expressed in EUR 1000's, 'No School' is a dummy variable for not completing secondary education, dependent variable is a measure of 'general willingness to take risks' on a 0–100 scale, 'Network(t-1)' is the size of the expatriate network one year before an individual migrates, expressed in 10,000 units. The sample is restricted to observations in years when the migrant network size was increasing.

Table 3: Summary statistics of main variables

Variable	Mean	Std. Dev.	Min.	Max.	N
Network(t-1)	61.597	59.669	0.052	211.022	3120
Risk	38.319	26.223	0	100	2648
Age	50.695	15.6	19	103	6387
Female	1.493	0.5	1	2	6387
Wages(1000s)	1.174	1.541	0	18	3095
Height	168.401	8.967	127	202	2882
No School	0.11	0.313	0	1	2021
gdp	2477.572	3892.333	97.158	44871.449	4777

Note: 'Network(t-1)' captures the number of migrants from a given country living in Germany one year before the individual migrated. The two main sources used to estimate the network size are the German Statistical Office and World Bank International Migrant Stock data (Schiff and Sjoblom 2010). 'Risk' is a re-scaled measure of general willingness to take risks scale taken from SOEP, ranging from 0 to 100, where 0 is the most risk-averse response. 'Wages' are monthly wages measured in thousands of Euros. 'No School' is a dummy variable for individuals who did not complete basic secondary education.

Table 4: Number of observations by country of birth

		Country Of Origin		
		Freq.	Percent	Cum.
1	Germany	42713	85.22	85.22
2	Turkey	1766	3.52	88.74
3	Italy	781	1.56	90.30
4	Ex-Yugoslavia	662	1.32	91.62
5	Poland	573	1.14	92.76
6	Greece	555	1.11	93.87
7	Spain	422	0.84	94.71
8	Russia	407	0.81	95.52
9	Kazakhstan	337	0.67	96.20
10	Romania	215	0.43	96.63
11	Eastern Europe	158	0.32	96.94
12	Croatia	118	0.24	97.18
13	Austria	98	0.20	97.37
14	Bosnia-Herzegovina	86	0.17	97.54
15	Czech Republic	77	0.15	97.70
Total		50122	100.00	

Note: Shows the 15 most represented countries of birth in the full sample. Source: German Socio-Economic Panel Study (SOEP)

Table 5: Risk aversion by country of birth

	Country of Birth					
	Ger	**Turk**	**Yugo**	**Italy**	**Other**	**Total**
Risk Averse	65%	72%	69%	69%	67%	65%
Risk Loving	35%	28%	31%	31%	33%	35%
Total	100%	100%	100%	100%	100%	100%
N	24,476	474	102	185	1,758	26,995

Source: SOEP

Note: 'Risk Averse' refers to individuals who answered between 1–5 on the willingness to take risks question, 'Risk Loving' refers to individuals who answered between 6–10 on the willingness to take risks question. For non-German-born people this includes all individuals who entered Germany between 1960 and 1995. The countries are Turkey, Former Yugoslavia, and Italy.

Table 6: Change of risk attitudes of individuals over time, migrant sample

	Risk Measures in Different Domains								
		Risk in General			Risk in Financial Matters			Risk in OccupationObs	
	Mean	Std. Err	Std. Dev	Mean	Std. Err	Std. Dev	Mean	Std. Err	Std. Dev
Measure 09	32.84	0.16	5.91	20.42	0.87	3.27	23.82	0.09	3.431408
Measure 04	37.84	0.17	6.33	17.33	0.10	3.57	25.50	0.11	4.141408
Difference	**-4.36**	0.01	0.42	**-3.09**	0.01	0.29	**-1.68**	0.02	0.711408
t	**-389.25**			**-391.96**			**-88.46**		
P value	**0.000**			**0.000**			**0.000**		

Note: The table shows a comparison of the mean level of willingness to take risks for a panel of individuals, measured in 2004 and 2009 after controlling for the effect of age on the risk measure. The measure is re-scaled from the original data and ranges from 0 to 100, with 0 being the most risk-averse. Results are shown for the general measure of risk, and willingness to take risks in financial matters and occupation. Source: German Socioeconomic Panel Study (SO