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Does language shape economic behavior?

A study of pension planning and financial wealth of immigrants in the Netherlands

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Abstract

Recent studies suggest that one characteristic of a language, future-time-reference (FTR), can have strong effects on how people think and make (economic) decisions. For instance, languages with no explicit distinction between future and present tense (weak-FTR languages, e.g., Dutch) make people more forward looking (Chen, 2013). Building on this idea and using survey data, this paper will examine (1) differences in pension planning and financial wealth among native Dutch and groups of immigrants with different home languages; (2) the relation between immigrants' Dutch proficiency and their pension planning and financial wealth. Empirical results show that immigrants who speak non-weak-FTR (i.e., strong-FTR) home languages think less about their retirement, are less likely to own and tend to own less financial wealth than immigrants who speak weak-FTR home languages and native Dutch. Furthermore, for immigrants who speak strong-FTR home languages, there is a significant positive effect of (weak-FTR) Dutch proficiency on their retirement planning. For immigrants who speak weak-FTR home languages, there is no significant effect of Dutch proficiency on their retirement planning. The paper helps to understand pension planning and decisions on financial wealth of Dutch natives and immigrants from different linguistic backgrounds, with an implication for the pension communication and contributions to the debate on whether language shapes thought in the field of linguistics and psychology.

Keywords: Economic behavior; Language; Immigrants; Pension planning; Financial wealth; Pension communication

1 Introduction

According to CBS (Statistics Netherlands), in 2014 immigration growth has reached more than 181,000, and in 2017 18.5% of the Dutch population will be older than 65. What is the retirement planning of immigrants? The increasing number of immigrants combined with the aging problem urges us to analyze differences in pension planning between native Dutch and immigrants.

Research on pension planning of immigrants is sparse. Topa, Moriano & Moreno (2012) propose that immigrants' financial preparation for retirement may be influenced by human capital, social-demographic and psychological factors. Furthermore, previous studies on pension planning emphasize the role of financial literacy (Lusardi & Mitchell, 2011). Individuals with higher level of financial literacy are more likely to develop a retirement plan (e.g., van Rooij, Lusardi & Alessie, 2012; Bucher-Koenen & Lusardi, 2011). Interestingly, a Swiss study shows that financial literacy, which is positively related with voluntary retirement saving, is lower among immigrants and women, but immigrants with German as native language have higher financial literacy than other immigrants (Brown & Graf, 2013).

Needless to say, linguistic barriers in the host country definitely constitute distinctive hurdles in economic and social integration of immigrants in the host country (Isphording, Ingo & Otten, 2014), but have you ever thought that the language they speak may influence their pension decisions?

Although both psychologists and linguists debate whether language shapes thought (Boroditsky, 2001), none of them has linked language to economic decisions. In an important recent study, Chen (2013) was the first to do this. He found that, independent of culture, language has an effect on saving. The idea is that languages making a stronger distinction between present and future (i.e. strong-future-time-reference languages) make individuals less aware of the future consequences of their current behavior, reducing forward looking behavior such as saving. Chen considered neither immigrants nor pension planning.

The innovative contribution of this paper is to empirically investigate the effect of home and host-country language on pension planning and financial wealth for Dutch natives and immigrants. In particular, it will examine the following research questions:

(Q1) What are the differences in pension planning and financial wealth among native Dutch and groups of immigrants in relation to differences in home language?

(Q2) How does the immigrants' Dutch proficiency shape this relation?

The aim of the paper is to better understand pension planning and decisions on financial wealth of Dutch natives and immigrants from different linguistic backgrounds, with an implication for pension schemes. The results will be also informative to theories in the field of linguistics, philosophy and cognitive psychology. It will contribute to understanding the links between cultural background and economic behavior, bringing together insights from different scientific domains - Economics, Cognitive Sciences, and Humanities.

The empirical results show that immigrants who speak strong-future-time-reference (i.e., strong-FTR) home languages have thought less about their retirement, are less likely to own and tend to own less financial wealth than immigrants who speak non-strong-FTR (i.e., weak-FTR) home languages and native Dutch. These findings are consistent with Chen (2013). Furthermore, for immigrants who speak strong-FTR home languages, there is a positive effect of Dutch (weak-FTR host-country language) proficiency on their pension planning. For immigrants who speak weak-FTR home languages, there is no significant effect of Dutch proficiency on their pension planning.

The paper proceeds as follows. Section 2 reviews the literature on language and thought, and the effect of one aspect of linguistic structure, future-time-reference (FTR), on economic behavior. Section 3 lays out the hypotheses related to the research questions, and details the data used for estimation. Section 4 investigates the relationship between a language's FTR and how much its speakers have thought about retirement, using an ordered logit model. Section 5 investigates the relationship between a language's FTR and its speakers' propensities to own financial wealth, using binary choice models. Section 6 analyzes the relationship between a language's FTR and the amount of financial wealth of its speakers, using censored regression models. Section 7 concludes.

2 Scientific background and rationale

We cannot escape languages in our life. One essential function of language is to convey our thoughts. However, speakers of different languages have to focus and encode strikingly different aspects of the world in order to use their language properly (Slobin, 1996). For example, to say "his cousin", in Chinese, the possessive pronouns "his" will not give away the gender (at least in speaking), because the pronunciation of "his" is exactly the same as that of "her". But the Chinese word "cousin" will specify the gender of the person referred to, as well as whether s/he is from the father's side or from the mother's side, and whether s/he is older or younger than the speaker. In Dutch, the word "cousin" specifies the gender whereas it does not distinguish whether s/he is a "cousin" or a "niece/nephew". These culture-embedded language differences can shape humans' thoughts on kinship (Levinson, 2012).

The hypothesis that language can influence thought is known as the "weak" Whorfian hypothesis, which proposes that the structure of one's language can influence one's understanding of the world and therefore can lead to a different perception of the world (Whorf, 1956). Admittedly, speaking differently does not necessarily lead to thinking differently, yet in the past decades, psychologists and linguists did find evidence showing that speakers of different languages have different ways of thinking, especially in how they perceive color, space, time, causality and the relationships to others (Boroditsky, 2011). Furthermore, research on bilingual speakers reveals that their languages are co-activated, which leads to bi-directional influences between first and foreign language (bilingual-minds theory, e.g., van Hell & Dijkstra, 2002).

Along the lines of the "weak" Whorfian hypothesis, if language affects one's cognition and cognition affects behavior (Costa, Foucart, Hayakawa, Aparici, Apesteguia, Heafner & Keysar, 2014), we should be able to find this trace in economic behavior. Recent studies have reported effects of one aspect of linguistic structure, future-time-reference (FTR), on economic behavior.

2.1 Future-time-reference (FTR) and future-oriented behavior

Strong-FTR languages, such as English and French, grammatically separate future and present (e.g., "It is raining now"; "It will rain tomorrow"), whereas weak-FTR languages, such as Dutch, do not have this feature (e.g., "Nu regent het"; "Morgen regent het") (Chen, 2013; Thieroff, 2000).

On the basis that the language one speaks can influence the way one conceptualizes time (e.g., Boroditsky, 2001; Gu, Mol, Hoetjes & Swerts, 2014), and that the sense of time has a profound influence on behavioral motivations (Cartensen, 2006), Chen (2013) proposes that strong-FTR languages make the future feel more distant and make individuals less aware of the future consequences of their current behavior, reducing future-oriented behavior such as saving (linguistic-saving theory). His cross-country analysis showed that speakers of weak-FTR languages indeed save more. Strikingly, within-country comparisons between individuals with identical background except for different home language revealed that, controlling for cultural values (whether saving is considered important and thriftiness is appreciated), language still influences saving (e.g., in Brussels, individuals who speak Dutch save more than those who speak French).

Following Chen (2013), Liang, Marquis, Renneboog & Sun (2014) and S. Chen, Cronqvist, Ni & Zhang (2015) showed that companies in weak-FTR language environments performed better in future-oriented activities such as corporate social responsibility, and held higher precautionary cash than strong-FTR companies. The effect was moderated if companies had greater exposure to various global languages. Experimental studies found that impatience is higher in strong-FTR than in weak-FTR counties (Becker & Falk, 2013). A behavioral study on children's inter-temporal choices in an Italian bilingual city (Meran) revealed that children speaking German (weak-FTR) were more patient and saved more than children speaking Italian (strong-FTR). The language effect was persistently significant even when controlling for demographics, IQ, risk attitudes, and cultural values. Interestingly, Italian-German bilingual children were less patient than German-speaking children but more patient than Italian-speaking children (Sutter, Angerer, Glatzle-Rutzler & Lergetporer, 2014).

Chen's linguistic-saving theory can be applied to retirement decisions. Based on Chen's theory, immigrants from countries with strong-FTR languages are expected to (1) think less about their retirement, since they feel future more distant; (2) save less and retire with less wealth, since current costs (foregone consumption) outweigh future revenues.

3 Hypotheses and data

Based on Chen's linguistic-saving theory, with respect to pension planning and financial wealth (the gross amount of financial assets), the following hypotheses are proposed:

(H1) Immigrants who speak strong-FTR home languages have thought less about retirement than immigrants who speak weak-FTR home languages and native Dutch;

(H2) Immigrants who speak strong-FTR home languages are less likely to own financial wealth than immigrants who speak weak-FTR home languages and native Dutch;

(H3) Immigrants who speak strong-FTR home languages tend to own less financial wealth than immigrants who speak weak-FTR home languages and native Dutch.

It is also interesting to consider the effect of immigrants' Dutch proficiency on their pension planning and financial wealth. Based on the bilingual-minds theory, the following hypotheses are proposed:

(H4) For immigrants speaking strong-FTR home languages, there is a positive effect of Dutch (weak-FTR host-country language) proficiency on their pension planning and decisions on financial wealth.

(H5) For immigrants speaking weak-FTR home languages, there is no significant effect of Dutch (weak-FTR host-country language) proficiency on their pension planning and decisions on financial wealth.

Survey data will be used. According to the CBS definition, immigrants include first generation (born abroad with at least one parent born abroad) and second generation immigrants (born in the Netherlands with at least one parent in the first generation). Other Dutch residents are classified as natives. The data are from the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands). The LISS panel, starting from November 2007, is a representative sample of Dutch individuals, covering language, origin, gender, education and various domains. In particular, a longitudinal survey about assets is conducted every two years, including a lot of information about assets. The waves were collected in 2008, 2010 and 2012. Respondents with missing information on language are excluded from the data, leading to an unbalanced panel of 12025 observations on 5074 individuals. In 2008, there was also a single-wave survey on the adequate old-age income, in which participants were asked how much they have thought about their retirement. Respondents with missing information on language are again excluded from the data, leading to a cross-section data of 1,151 individuals.

Table 1 shows a description of the data with summary statistics of all variables in 2008. Following the existing literature (e.g., Lusardi & Mitchell, 2007; Lusardi & Mitchell, 2009), $ThouRetire$ can be regarded as a retirement planning measure, which ranges from 1 (The individual has hardly thought about retirement at all) to 4 (The individual has thought a lot about retirement)[1]. $Ownfin$ is a binary variable at the individual level, which equals to 1 if an individual owns financial wealth. $Logfin$ is a left-censored variable at the individual level, which equals to the log transformation of an individual's financial wealth if s/he owns positive financial wealth (otherwise equals 0). Financial wealth (the gross amount of financial assets) of an individual is the sum of his/her riskless assets (e.g., current accounts, savings accounts, term deposit accounts, savings bonds or savings certificates), single-premium insurance policy, life annuity insurance, endowment insurance (not linked to a mortgage), and investments (e.g., growth funds, share funds, bonds, debentures, stocks, options, warrants).

The distinction of language is the same as that in Chen (2013)'s paper. Dutch proficiency, which ranges from 1 (low level) to 3 (high level), is derived as an average of Dutch speaking proficiency and Dutch reading proficiency. Education level ranges from 1 (low level) to 6 (high level) and it can reflect the level of financial literacy to some extent. Direct information about financial literacy is not available in the LISS panel, but can be collected in the future.

Following Chen (2013), $trust$ is also added as an independent variable, which ranges from 0 (one cannot be too careful in dealing with people) to 10 (most people can be trusted). It is one of the most studied variables in the large body of literature on social capital. Four origin dummies ($west1$, $west2$, $nonwest1$ and $nonwest2$) are used to account for the potential non-linguistic cultural factors of four different immigrants groups.

[1] The original question wording in the questionnaire is as follows: "How much have you thought about retirement?" The corresponding four alternatives are: (1) 1 a lot; (2) 2 some; (3) 3 a little; (4) 4 hardly at all.

Table 1 Descriptives

Variable	Description	Mean	SD
Dependent variables			
ThouRetire	(1~4) how much the individual has thought about retirement	2.168	0.789
Ownfin	(1, 0) if the individual owns financial wealth	0.825	0.380
Logfin	Log transformation of financial wealth of the individual	6.281	4.520
Independent variables			
Strongftr	(1,0) if the individual speaks a strong-FTR home language[2]	0.0285	0.166
Dutchprof	(1~3) Dutch proficiency of the individual	2.884	0.284
Logincome	Log transformation of income[3] of the individual	6.309	2.390
Female	(1, 0) if being female	0.536	0.499
Age	Age of the individual	48.359	15.975
Edu	(1~6) education level of the individual	3.511	1.485
Trust	(0~10) to what degree that most people can be trusted	6.057	2.099
Househead	(1, 0) if being household head[4]	0.526	0.499
West1	(1, 0) if being first generation immigrant with western background	0.0250	0.156
West2	(1, 0) if being second generation immigrant with western background	0.0473	0.212
Nonwest1	(1, 0) if being first generation immigrant with non-western background	0.0272	0.163
Nonwest2	(1, 0) if being second generation immigrant with non-western background	0.0112	0.105

Source: LISS panel, 2008, sample of Dutch natives and immigrants.

[2] Here the “home language” is equivalent to the “first language”. The original language variable is “language spoken at home”. However, this might be uninformative or misleading. For example, if an individual, who was born in England, being 40 years old now, answered that s/he has been lived in the Netherlands for 5 years and speaks Dutch at home, then English is regarded as his/her first language. In such a way, some adjustments are made on “language spoken at home”.

[3] It is noted in the LISS panel (http://www.lissdata.nl/dataarchive/study_units/view/322) that: “Since some people prefer not to make their income information available to CentERdata, a 0 (zero) can mean two different things: (1) that there is no income at all, or (2) that a panel member does not know what the income is or does not want to make that information available to us. In the second case, panel members ought to indicate that they do not know what the income is. Unfortunately, not all panel members do so, so that there are and continue to be panel members that enter (0) while they actually do have an income. It is impossible to determine who these panel members are, however.” (Codebook_BackgroundVariables_EN_8.0, p.5/8) The quality of *logincome* may influence final regression results.

[4] It is noted in the LISS panel (http://www.lissdata.nl/dataarchive/study_units/view/322) that: “The household head is the person whose name appears on the rent contract or purchase deed of the house. If the contract or deed carries more than one name, the household head is the person with the highest income.” (Codebook_BackgroundVariables_EN_8.0, p.3/8)

It is possible that there exists a joint property of husband and wife in the household and that the household head owns more joint property than the other household members. However, it is hard to do analyses related to financial wealth at the household level. First, there will be less variation in the variable $ownfin$ at the household level than that at the individual level. If the financial wealth is considered at the household level, 89.39%, 94.72% and 94.72% of households in the sample of Dutch natives and immigrants own financial wealth in wave 1, wave 2 and wave 3 respectively. Second, since there is no available method to measure FTR in bilingual households, bilingual households (including 241 observations) have to be excluded from the panel if the analysis is conducted at the household level, which result in fewer observations of immigrants. Furthermore, because for many households some household members are not in the panel, it may be not appropriate to simply add the financial wealth of available household members together or take the average. Thus, in this paper, all analyses related to financial wealth will be conducted at the individual level, adding $househead$ and interaction terms between $househead$ and origin dummies as independent variables.[5]

4 FTR and Dutch residents' retirement planning

This section tests hypotheses H1, H4 and H5 using the survey data. It investigates the relationship between a language's FTR and how much its speakers have thought about retirement, where the dependent variable is an ordered variable $ThouRetire_i$, which ranges from 1 (The individual has hardly thought about retirement at all) to 4 (The individual has thought a lot about retirement). The analysis is therefore conducted with an ordered logit model for cross-section data. The software used to do estimation is Stata 12.

4.1 Ordered logit model for cross-section data

The basic setting of an ordered logit model is

[5] The subsample of household heads only will be used to run regressions at the household level, and the results will be presented in Appendix A. Nevertheless, the results are likely to be biased, because the financial wealth of the household head may be not representative of the whole household. For instance, for the households with male household heads (which is very common in the data), household wives of some countries prefer to stay at home and do housework whereas household wives of some other countries are more likely to work and earn an income. Surveys on US immigrants showed that females from some countries do exhibit lower labor force participation and hours worked than those from some other countries (Gay, Hicks, Santacreu-Vasut & Shoham, A., 2015). Thus the financial wealth of the household can be underestimated by that of the household head if there are other household members participating in the labor market.

$$ThouRetire_i^* = strongftr_i\beta_1 + dutchprof_i\beta_2 + logincome_i\beta_3 + female_i\beta_4 + age_i\beta_5 + edu_i\beta_6 + west1_i\beta_7 + west2_i\beta_8 + nonwest1_i\beta_9 + nonwest2_i\beta_{10} + trust_i\beta_{11} + FtrDutch_i\beta_{12} + \epsilon_i$$

$$FtrDutch_i = strongftr_i * dutchprof_i$$

$$ThouRetire_i = \begin{cases} 1 & if\ ThouRetire_i^* \le m_1 \\ 2 & if\ m_1 < ThouRetire_i^* \le m_2 \\ 3 & if\ m_2 < ThouRetire_i^* \le m_3 \\ 4 & if\ m_3 < ThouRetire_i^* \end{cases}$$

$$x_i = (\, strongftr_i\ dutchprof_i\ logincome_i\ trust_i\ \ female_i\ age_i\ edu_i\ \ west1_i\ west2_i\ nonwest1_i\ nonwest2_i\ FtrDutch_i)'$$

$$\epsilon_i \sim\ logistic, \text{i. i. d., independent of } x_i$$

where x_i includes all explanatory variables, and $\beta's$ are coefficients to be estimated. The continuous $ThouRetire_i^*$ is unobservable. Only the ordered variable $ThouRetire_i$ is observed.

4.2 Results and discussions

Table 2 shows estimation results of an ordered logit model with respect to FTR and Dutch residents' retirement planning. The ordered dependent variable $ThouRetire_i$ ranges from 1 (The individual has hardly thought about retirement at all) to 4 (The individual has thought a lot about retirement). In both columns (1) and (2), the estimated coefficient of $strongftr$ is significantly negative at the 5% significant level, which means that immigrants who speak strong-FTR home languages have thought less about retirement than immigrants who speak weak-FTR home languages and native Dutch, ceteris paribus. The effect of $strongftr$ on retirement planning is negative, which is in line with Chen's linguistic-saving theory.

Four origin dummies ($west1$, $west2$, $nonwest1$ and $nonwest2$) are used to account for the potential non-linguistic cultural factors of four different immigrants groups. Alternatively, three origin dummies can be constructed: $west$ ((1, 0) if the individual has a western background), $gene1$ ((1, 0) if being a first generation immigrant) and $gene2$ ((1, 0) if being a second generation immigrant). The former way of four origin dummies allows the interaction between background and generation whereas the latter way of three origin dummies does not. Wald test 1 in column (1) helps to make clear whether there is an interaction between background and generation. The null hypothesis that $\beta_{west2} - \beta_{west1} = \beta_{nonwest2} - \beta_{nonwest1}$ cannot be rejected at the 5% significant level, since p-value is larger than 0.05. There is not enough evidence to conclude that the difference in retirement planning between first generation and second generation immigrants with western background is different from the difference in retirement planning between first generation and second generation immigrants with non-western background, keeping other variables unchanged. In other words, there is not enough evidence to conclude that the difference in retirement planning between western and non-western first-generation immigrants is different from the difference in retirement planning between western and non-western second-generation immigrants, keeping other variables unchanged.

To investigate the effect of immigrants' Dutch proficiency on their retirement planning and to test hypotheses H4 and H5, column (3) further adds $dutchprof$ and $FtrDutch$ (i.e., the interaction between $strongftr$ and $dutchprof$) as independent variables. The estimated coefficient of $dutchprof$ is not significant at the 10% significant level. This implies that, for immigrants who speak weak-FTR home languages, there is no significant effect of Dutch (weak-FTR) proficiency on their retirement planning, as it is predicted in section 3.

Furthermore, on the one hand, the null hypothesis of the Wald test 2 that $\beta_{strongftr} + \beta_{FtrDutch} = 0$ is rejected at the 1% significant level, and $\hat{\beta}_{strongftr} + \hat{\beta}_{FtrDutch} < 0$. This means that, for immigrants with the low level of Dutch proficiency (i.e., $dutchprof = 1$), immigrants who speak strong-FTR home languages have thought less about retirement than immigrants who speak weak-FTR home languages, ceteris paribus. In this case, the effect of $strongftr$ on retirement planning is negative, which is in line with Chen's linguistic-saving theory. On the other hand, the null hypothesis of the Wald test 3 that $\beta_{strongftr} + 3\beta_{FtrDutch} = 0$ cannot be rejected at the 10% significant level, since p-value is larger than 0.1. This means that, for immigrants with the high level of Dutch proficiency (i.e., $dutchprof = 3$), there is no significant effect of $strongftr$ on the retirement planning. It seems that the effect of $strongftr$ depends on the Dutch proficiency.

Table 2 FTR and Dutch residents' retirement planning

	(1) Sample of Dutch natives and immigrants	(2) Sample of immigrants	(3) Sample of immigrants
Strongftr	-1.265**	-1.361**	-8.732***
	(0.532)	(0.604)	(2.598)
FtrDuctch			3.186***
			(1.035)
Dutchprof			-0.953
			(0.726)
Logincome	0.081***	0.199*	0.182
	(0.0305)	(0.11)	(0.113)
Female	-0.391***	0.217	0.0412
	(0.124)	(0.46)	(0.478)
Age	0.0599***	0.072***	0.0788***
	(0.0058)	(0.0227)	(0.0235)
Edu	0.118***	0.101	0.0601
	(0.0416)	(0.142)	(0.149)
Trust	-0.0661**	0.114	0.194
	(0.0295)	(0.119)	(0.127)
West1	0.753	1.337	1.187
	(0.474)	(1.153)	(1.205)
West2	0.045	0.544	0.771
	(0.3)	(1.076)	(1.117)
Nonwest1	0.918*	1.806	2.126*
	(0.475)	(1.156)	(1.198)
Nonwest2	-0.306		
	(0.91)		
m_1	1.618***	4.452**	2.163
	(0.429)	(1.76)	(2.25)
m_2	4.226***	7.864***	5.895**
	(0.447)	(1.919)	(2.348)
m_3	6.243***	9.704***	7.876***
	(0.468)	(2.01)	(2.417)
Wald test 1 (p-value)	0.638		
Wald test 2 (p-value)			0.001
Wald test 3 (p-value)			0.337
Wald test 4 (p-value)			0.002
Log likelihood	-1260.93	-91.235	-84.874
Observations	1,151	95	95

Notes: Data source: LISS panel. The dependent variable is an ordered variable $ThouRetire_i$, which ranges from 1 (The individual has hardly thought about retirement at all) to 4 (The individual has thought a lot about retirement). $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. $Dutchprof$ (i.e., Dutch proficiency) ranges from 1 (low level) to 3 (high level). As for the Wald test 1, H0: $\beta_{west2} - \beta_{west1} = \beta_{nonwest2} - \beta_{nonwest1}$. As for the Wald test 2, H0: $\beta_{strongftr} + \beta_{FtrDutch} = 0$. As for the Wald test 3, H0: $\beta_{strongftr} + 3\beta_{FtrDutch} = 0$. As for the Wald test 4, H0: $\beta_{FtrDutch} + \beta_{dutchprof} = 0$. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

One possible explanation for this interaction between $strongftr$ and Dutch proficiency is that: when the level of Dutch proficiency is low, immigrants are mostly influenced by their home languages; when the level of Dutch proficiency is high, immigrants are also very likely to be influenced by their host-country language Dutch. In other words, Dutch (weak-FTR) as a foreign language is activated and exerts some influence on the retirement planning. This is consistent with the bilingual-minds theory (van Hell & Dijkstra, 2002) that languages that immigrants speak can be co-activated. Alternatively, it is reasonable to assume that immigrants with high Dutch proficiency have more exposure to the Dutch culture, therefore it can be that their retirement planning are greatly influenced by the Dutch culture rather than their host-country language Dutch. However, in the Dutch culture, people used to trust the pension fund and leave retirement planning to the managers of their pension fund (van Dalen, Henkens & Hershey, 2010). That means the Dutch culture will reduce the extent to which immigrants' thinking about their retirement. In other words, for immigrants who speak strong-FTR home languages, there should be a negative effect of (weak-FTR) Dutch proficiency on retirement planning. Nevertheless, the null hypothesis of the Wald test 4 that $\beta_{FtrDutch} + \beta_{dutchprof} = 0$ is rejected at the 1% significant level, and $\hat{\beta}_{FtrDutch} + \hat{\beta}_{dutchprof} > 0$. This means that, for immigrants who speak strong-FTR home languages, there is still a significant positive effect of (weak-FTR) Dutch proficiency on retirement planning, even it is moderated by the potential Dutch culture. Thus it is not the Dutch culture but the host-country language Dutch that influences immigrants' retirement planning. This result provides empirical evidence for the bilingual-minds theory, which claims that there are bi-directional influences between different languages of immigrants.

5 FTR and Dutch residents' propensities to own financial wealth

This section tests hypotheses H2, H4 and H5 using the survey data. It investigates the relationship between a language's FTR and its speakers' propensities to own financial wealth, where the dependent variable is a binary variable $ownfin_{it}$ which equals to 1 if individual i owns financial wealth in wave t. The analysis is conducted at the individual level with binary choice models for panel data, including static fixed-effects logit model[6], static random-effects logit model, static quasi-fixed-effects logit model, dynamic random-effects logit model and dynamic quasi-fixed-effects logit model. The software used to do estimation is Stata 12.

[6] The dynamic fixed-effects logit model cannot be used here, because dynamic fixed-effects logit model needs data with four periods and there are only three waves in the available data.

5.1 Binary choice models for panel data

5.1.1 Static logit models for panel data

The basic setting of a static logit model is

$$ownfin_{it}^{*} = \beta_0 + strongftr_i\beta_1 + dutchprof_{it}\beta_2 + logincome_{it}\beta_3 + female_i\beta_4 + age_i\beta_5 + edu_i\beta_6 + west1_i\beta_7 + west2_i\beta_8 + nonwest1_i\beta_9 + nonwest2_i\beta_{10} + trust_{it}\beta_{11} + FtrDutch_{it}\beta_{12} + househead_{it}\beta_{13} + \alpha_i + \epsilon_{it}$$

$$FtrDutch_{it} = strongftr_i * dutchprof_{it}$$

$$ownfin_{it} = \begin{cases} 1 & \text{if } ownfin_{it}^{*} > 0 \\ 0 & \text{if } ownfin_{it}^{*} \le 0 \end{cases}, t = 1,2,3$$

$$x_{it} = (1\ strongftr_i\ dutchprof_{it}\ logincome_{it}\ trust_{it}\ \ female_i\ age_i\ edu_i\ \ west1_i\ west2_i\ nonwest1_i\ nonwest2_i\ FtrDutch_{it}\ househead_{it})'$$

$$\epsilon_{it} \sim logistic, \text{i. i. d.}, \text{independent of } (x_{i1}, x_{i2}, x_{i3})$$

where α_i is an unobserved individual effect, x_{it} includes all explanatory variables, and $\beta's$ are coefficients to be estimated. Only the sign of the variable $ownfin_{it}^{*}$ is observed, which is coded as binary variable $ownfin_{it}$. $ownfin_{it}$ equals to 1 if individual i owns financial wealth in wave t.

In a static fixed-effects logit model, as for α_i, it is assumed that:

$$\alpha_i\text{: no assumption on } \alpha_i$$

In a static random-effects logit model, as for α_i, it is assumed that:

$$\alpha_i \sim N(0, \sigma_\alpha^2), \text{independent of } (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}) \text{ and } (x_{i1}, x_{i2}, x_{i3})$$

In a static quasi-fixed-effects logit model, as for α_i, it is assumed that:

$$\alpha_i = \delta avelogincome_i + \tilde{\alpha}_i$$

$$avelogincome_i \text{ is the mean over time of } logincome$$

$$\tilde{\alpha}_i \sim N\left(0, \sigma_{\tilde{\alpha}}^2\right), \text{independent of } (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}) \text{ and } (x_{i1}, x_{i2}, x_{i3})$$

The coefficient β_k can be interpreted using the marginal effect of explanatory variable x_{itk}:

$$\frac{\partial P(ownfin_{it} = 1|x_{it}, \alpha_i)}{x_{itk}} = P(ownfin_{it} = 1|x_{it}, \alpha_i) * [1 - P(ownfin_{it} = 1|x_{it}, \alpha_i)] * \beta_k$$

The marginal effect can be calculated for an average observation, where $P(ownfin_{it} = 1|x_{it}, \alpha_i)$ is replaced by $\overline{\text{ownfin}} = 0.825$ according to Table 1.

The importance of unobserved heterogeneity is measured by

$$\rho = \frac{Var(\alpha_i)}{Var(\alpha_i) + Var(\epsilon_{it})}$$

For a logit model, $Var(\epsilon_{it}) = \frac{\pi^2}{3}$.

5.1.2 Dynamic logit models for panel data

The basic setting of a dynamic logit model using Wooldridge approach (Wooldridge, 2005) is

$$\begin{aligned} ownfin_{it}^{*} = \beta_0 &+ \gamma ownfin_{i,t-1} + strongftr_i\beta_1 + dutchprof_{it}\beta_2 + logincome_{it}\beta_3 + female_i\beta_4 \\ &+ age_i\beta_5 + edu_i\beta_6 + west1_i\beta_7 + west2_i\beta_8 + nonwest1_i\beta_9 + nonwest2_i\beta_{10} \\ &+ trust_{it}\beta_{11} + FtrDutch_{it}\beta_{12} + househead_{it}\beta_{13} + \alpha_i + \epsilon_{it} \end{aligned}$$

$$FtrDutch_{it} = strongftr_i * dutchprof_{it}$$

$$ownfin_{it} = \begin{cases} 1 & \text{if } ownfin_{it}^{*} > 0 \\ 0 & \text{if } ownfin_{it}^{*} \leq 0 \end{cases}, t = 2{,}3, ownfin_{i1} \text{ is treated as given}$$

$$\begin{aligned} x_{it} = (1\ &strongftr_i\ dutchprof_{it}\ logincome_{it}\ trust_{it}\ \ female_i\ age_i\ edu_i\ west1_i\ west2_i \\ &nonwest1_i\ nonwest2_i\ FtrDutch_{it}\ househead_{it})' \end{aligned}$$

$$\epsilon_{i2}, \epsilon_{i3}, logistic, \text{i.i.d.}, \text{independent of } (\ x_{i2}, x_{i3}) \text{ and } \ ownfin_{i1}$$

where α_i is an unobserved individual effect and γ is a parameter of state dependence. Only the sign of the variable $ownfin_{it}^{*}$ is observed, which is coded as binary variable $ownfin_{it}$. $ownfin_{it}$ equals to 1 if individual i owns financial wealth in wave t.

In a dynamic random-effects logit model, as for α_i, it is assumed that:

$$\alpha_i = \lambda ownfin_{i1} + \tilde{\alpha}_i$$

$$\tilde{\alpha}_i \sim N(0, \sigma_{\tilde{\alpha}}^2), \text{independent of } (\epsilon_{i2}, \epsilon_{i3}), (x_{i2}, x_{i3}) \text{ and } \ ownfin_{i1}$$

In a dynamic quasi-fixed-effects logit model, as for α_i, it is assumed that:

$$\alpha_i = \lambda ownfin_{i1} + \delta avelogincome_i + \tilde{\alpha}_i$$

$$avelogincome_i \text{ is the mean over time of } logincome$$

$$\tilde{\alpha}_i \sim N(0, \sigma_{\tilde{\alpha}}^2), \text{independent of } (\epsilon_{i2}, \epsilon_{i3}), (x_{i2}, x_{i3}) \text{ and } \ ownfin_{i1}$$

The calculation of the marginal effect of explanatory variable x_{itk} and the importance of unobserved heterogeneity is similar to that in static logit models.

5.2 Results and discussions

Table 3 shows estimation results of binary choice models for the sample of Dutch natives and immigrants. The binary dependent variable $ownfin_{it}$ equals to 1 if individual i owns financial wealth in wave t. The Hausman test in column (2) helps to choose between static RE logit and static FE logit model. The null hypothesis (static RE logit model) cannot be rejected at the 5% significant level, since p-value=0.0581>0.05. Static QFE logit model in column (3) allows the individual effect to depend upon the (individual specific) mean over time of $logincome$. The estimated coefficient of $avelogincome$ is significant at the 5% significant level, which means that the individual effect is correlated with $logincome$. Thus the static QFE logit model is preferred among static RE, FE and QFE logit models.

Static QFE logit model in column (4) further adds time dummies as additional independent variables. The Wald test 1 tests the joint significance of time dummies. The null of no relationship is rejected at the 5% significant level, since p-value=0.000<0.05. Thus time dummies should be added to static QFE logit model. Columns (5) and (6) show estimation results of dynamic QFE and RE logit models. The estimated coefficient of lag_ownfin is not significant at the 5% significant level in both columns, which means that there is no empirical evidence of state dependence. Thus the static QFE logit model in column (4) is used for further analyses.

In column (4) of Table 3, the unobserved heterogeneity is significantly present. $\hat{\sigma}_{\tilde{\alpha}}$ is significant at the 1% significant level. The importance of unobserved heterogeneity is

$$\hat{\rho} = \frac{\widehat{Var}(\alpha_i)}{\widehat{Var}(\alpha_i) + Var(\epsilon_{it})} = \frac{\widehat{Var}(\delta avelogincome_i + \tilde{\alpha}_i)}{\widehat{Var}(\delta avelogincome_i + \tilde{\alpha}_i) + \frac{\pi^2}{3}}$$

$$= \frac{\hat{\delta}^2 \widehat{Var}(avelogincome_i) + \hat{\sigma}^2_{\tilde{\alpha}}}{\hat{\delta}^2 \widehat{Var}(avelogincome_i) + \hat{\sigma}^2_{\tilde{\alpha}} + \pi^2/3} = \frac{0.15^2 * 2^2 + 1.93^2}{0.15^2 * 2^2 + 1.93^2 + \pi^2/3} \approx 0.537$$

The estimated coefficient of $strongftr$ is significantly negative at the 10% significant level. The corresponding marginal effect is

$$\hat{P}(ownfin_{it} = 1|x_{it}, \alpha_i) * [1 - \hat{P}(ownfin_{it} = 1|x_{it}, \alpha_i)] * \hat{\beta}_{strongftr}$$

$$= 0.825 * 0.175 * (-0.598) \approx -0.086$$

This means for an average person, if s/he speaks a strong-FTR home language rather than a weak-FTR home language, then s/he is 8.6% less likely to own financial wealth, keeping other variables unchanged. The effect of $strongftr$ on the propensity to own financial wealth is negative, which is in line with Chen's linguistic-saving theory.[7]

Four origin dummies ($west1$, $west2$, $nonwest1$ and $nonwest2$) are used here to account for the potential non-linguistic cultural factors of four different immigrants groups. Alternatively, three origin dummies can be constructed: $west$ ((1, 0) if the individual has a western background), $gene1$ ((1, 0) if being a first generation immigrant) and $gene2$ ((1, 0) if being a second generation immigrant). The former way of four origin dummies allows the interaction between background and generation whereas the latter way of three origin dummies does not. Wald test 2 helps to make clear whether there is an interaction between background and generation. The null hypothesis that $\beta_{west2} - \beta_{west1} = \beta_{nonwest2} - \beta_{nonwest1}$ cannot be rejected at the 5% significant level, since p-value is larger than 0.05. There is not enough evidence to conclude that the difference in the propensity to own financial wealth between first generation and second generation immigrants with western background is different from the difference in the propensity to own financial wealth between first generation and second generation immigrants with non-western background, keeping other variables unchanged. In other words, there is not enough evidence to conclude that the difference in the propensity to own financial wealth between western and non-western first-generation immigrants is different from the difference in the propensity to own financial wealth between western and non-western second-generation immigrants, keeping other variables unchanged.

[7] In Appendix A, Table A.1 shows corresponding estimation results of binary choice models for the subsample of household heads of Dutch natives and immigrants. The estimated coefficient of $strongftr$ is not significant at the 10% significant level in all columns. However, the results are likely to be biased (see Footnote 5). Future research needs to expand the information in the LISS panel with information from administrative records on wealth from Statistics Netherlands, so that the financial wealth of the whole household can be calculated precisely.

Table 3 FTR and the propensity to own financial wealth: sample of Dutch natives and immigrants

	Static logit models				Dynamic logit models	
	(1) FE	(2) RE	(3) QFE	(4) QFE	(5) QFE	(6) RE
Strongftr		-0.605*	-0.583*	-0.598*	-0.351	-0.362
		(0.335)	(0.336)	(0.356)	(0.489)	(0.500)
Lag_ownfin					0.184	0.0783
					(0.279)	(0.261)
Ownfin_0					2.236***	2.353***
					(0.360)	(0.349)
Logincome	0.0542	0.134***	0.0565	0.0104	0.0252	0.0986***
	(0.0437)	(0.0207)	(0.0432)	(0.0448)	(0.0727)	(0.0308)
Avelogincome			0.1000**	0.153***	0.0864	
			(0.0490)	(0.0509)	(0.0793)	
Female		-0.325***	-0.310***	-0.352***	-0.193	-0.210
		(0.118)	(0.118)	(0.124)	(0.168)	(0.172)
Age		-0.0117***	-0.0123***	-0.0144***	-0.0113**	-0.0109**
		(0.00330)	(0.00333)	(0.00351)	(0.00478)	(0.00483)
Edu		0.380***	0.373***	0.395***	0.238***	0.249***
		(0.0369)	(0.0371)	(0.0392)	(0.0540)	(0.0548)
Trust	0.000198	0.0467**	0.0476**	0.0390*	0.00674	0.00638
	(0.0301)	(0.0204)	(0.0205)	(0.0215)	(0.0312)	(0.0317)
Househead	0.100	0.337***	0.316**	0.290**	0.430**	0.458**
	(0.380)	(0.129)	(0.130)	(0.137)	(0.185)	(0.188)
Constant		1.267***	1.184***	1.815***	0.449	0.597
		(0.259)	(0.262)	(0.288)	(0.419)	(0.412)
Origin dummies	No	Yes	Yes	Yes	Yes	Yes
Househead*Origin dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	No	No	No	Yes	Yes	No
$\hat{\sigma}_\alpha$		1.780***				
		(0.0898)				
$\hat{\sigma}_{\tilde{\alpha}}$			1.786***	1.928***	1.660***	1.731***
			(0.0902)	(0.0965)	(0.259)	(0.248)
Hausman test (p-value)		0.0581				
Wald test 1 (p-value)				0.000	0.333	
Wald test 2 (p-value)				0.773		
Log likelihood	-706.992	-3564.155	-3562.082	-3467.694	-1529.019	-1530.137
Observations	1,956	10,801	10,801	10,801	6,006	6,006
Individuals	712	4,725	4,725	4,725	3,535	3,535

Notes: Data source: LISS panel, sample of Dutch natives and immigrants. The dependent variable is a binary variable $ownfin_{it}$ which equals to 1 if individual i owns financial wealth in wave t. $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. "Househead*Origin dummies" means interaction terms between $househead$ and origin dummies ($west1$, $west2$, $nonwest1$ and $nonwest2$). As for the Hausman test in column (2), H0: RE model, H1: FE model. It looks at coefficients of all time-varying variables. The Wald test 1 tests the joint significance of time dummies. As for the Wald test 2, H0: $\beta_{west2} - \beta_{west1} = \beta_{nonwest2} - \beta_{nonwest1}$. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

To investigate the effect of immigrants' Dutch proficiency on their propensities to own financial wealth and to test hypotheses H4 and H5, Table 4 further adds $dutchprof$ and $FtrDutch$ (i.e., the interaction between $strongftr$ and $dutchprof$) as independent variables and use the sample of immigrants only. The binary dependent variable is still $ownfin_{it}$, which equals to 1 if individual i owns financial wealth in wave t. The Hausman test in column (2) helps to choose between static RE logit and static FE logit model. The null hypothesis (static RE logit model) cannot be rejected at the 5% significant level, since p-value=0.334>0.05. Static QFE logit model in column (3) allows the individual effect to depend upon the (individual specific) mean over time of $logincome$. The estimated coefficient of $avelogincome$ is not significant at the 10% significant level. Thus the static RE logit model is preferred among static RE, FE and QFE logit models.

Static RE logit model in column (4) further adds time dummies as additional independent variables. The Wald test 1 tests the joint significance of time dummies. The null of no relationship is rejected at the 5% significant level, since p-value=0.000<0.05. Thus time dummies should be added to static RE logit model.

Columns (5) and (6) show estimation results of dynamic RE and QFE logit models. The estimated coefficient of lag_ownfin is significant at the 1% significant level, which means that there is empirical evidence of (positive) state dependence. Thus the dynamic logit models are preferred than the static logit models. Dynamic QFE logit model in column (6) allows the individual effect to depend upon the (individual specific) mean over time of $logincome$. The estimated coefficient of $avelogincome$ is not significant at the 10% significant level. Thus the dynamic RE logit model is used for further analyses.

In column (5), the estimated coefficient of $ownfin\_0$ is not significant at the 10% significant level, so the null hypothesis of no correlation between individual effects and the initial value of $ownfin$ cannot be rejected. Furthermore, $\hat{\sigma}_{\tilde{\alpha}}$ is not significant at the 10% significant level. A pooled logit regression is used to make a robustness check. It is assumed that there is no individual effect (unobserved heterogeneity) and lag_ownfin is included as an exogenous independent variable. The results are similar to those in column (5).

Table 4 FTR and the propensity to own financial wealth: sample of immigrants

	Static logit models				Dynamic logit models	
	(1) FE	(2) RE	(3) QFE	(4) RE	(5) RE	(6) QFE
Strongftr		0.163	0.217	0.549	0.924	1.039
		(1.443)	(1.451)	(1.543)	(2.017)	(2.063)
FtrDutch	0.787	-0.186	-0.196	-0.352	-0.347	-0.387
	(1.102)	(0.539)	(0.542)	(0.576)	(0.763)	(0.780)
Dutchprof	-0.980	0.459	0.440	0.496	0.530	0.544
	(0.854)	(0.405)	(0.408)	(0.432)	(0.564)	(0.577)
Lag_ownfin					1.502***	1.482***
					(0.530)	(0.540)
Ownfin_0					0.592	0.661
					(0.618)	(0.644)
Logincome	-0.0215	0.103**	-0.0407	0.104**	0.187***	-0.000406
	(0.102)	(0.0492)	(0.103)	(0.0525)	(0.0698)	(0.171)
Avelogincome			0.189			0.237
			(0.119)			(0.199)
Female		-0.190	-0.158	-0.266	-0.385	-0.380
		(0.265)	(0.267)	(0.284)	(0.367)	(0.375)
Age		-0.00260	-0.00452	-0.00648	0.0124	0.0105
		(0.00866)	(0.00879)	(0.00928)	(0.0114)	(0.0117)
Edu		0.241***	0.234***	0.263***	0.334***	0.331***
		(0.0785)	(0.0788)	(0.0846)	(0.118)	(0.121)
Trust	-0.00416	0.0454	0.0460	0.0437	0.0382	0.0369
	(0.0671)	(0.0459)	(0.0461)	(0.0490)	(0.0666)	(0.0683)
Househead	0.810	0.478	0.385	0.622	0.122	-0.0416
	(1.264)	(0.750)	(0.756)	(0.800)	(1.325)	(1.371)
Constant		-1.285	-1.359	-0.686	-3.626*	-3.674*
		(1.314)	(1.324)	(1.421)	(1.862)	(1.915)
Origin dummies	No	Yes	Yes	Yes	Yes	Yes
Househead*Origin dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	No	No	No	Yes	Yes	Yes
$\hat{\sigma}_{\alpha}$		1.405***		1.573***		
		(0.220)		(0.237)		
$\hat{\sigma}_{\tilde{\alpha}}$			1.416***		0.762	0.855
			(0.221)		(0.696)	(0.672)
Hausman test (p-value)		0.334				
Wald test 1 (p-value)				0.000	0.0345	0.0412
Wald test 2 (p-value)					0.652	
Wald test 3 (p-value)					0.826	
Wald test 4 (p-value)					0.725	
Log likelihood	-104.542	-504.030	-502.733	-483.221	-187.873	-187.136
Observations	294	1,121	1,121	1,121	604	604
Individuals	109	513	513	513	358	358

Notes: Data source: LISS panel, sample of immigrants. The dependent variable is a binary variable $ownfin_{it}$ which equals to 1 if individual i owns financial wealth in wave t. $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. $Dutchprof$ (i.e., Dutch proficiency) ranges from 1 (low level) to 3 (high level). "Househead*Origin dummies" means interaction terms between $household$ and origin dummies ($west1$, $west2$, $nonwest1$ and $nonwest2$). As for the Hausman test in column (2), H0: RE model, H1: FE model. It looks at the coefficients of all time-varying variables. The Wald test 1 tests the joint significance of time dummies. As for the Wald test 2, H0: $\beta_{strongftr} + \beta_{FtrDutch} = 0$. As for the Wald test 3, H0: $\beta_{strongftr} + 3\beta_{FtrDutch} = 0$. As for the Wald test 4, H0: $\beta_{FtrDutch} + \beta_{dutchprof} = 0$. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In column (5) of Table 4, the null hypothesis of the Wald test 2 that $\beta_{strongftr} + \beta_{FtrDutch} = 0$ cannot be rejected at the 10% significant level. This means that, for immigrants with the low level of Dutch proficiency (i.e., $dutchprof = 1$), there is no significant effect of $strongftr$ on their propensities to own financial wealth. Furthermore, the null hypothesis of the Wald test 3 that $\beta_{strongftr} + 3\beta_{FtrDutch} = 0$ cannot be rejected at the 10% significant level, since p-value is larger than 0.1. This means that, for immigrants with the high level of Dutch proficiency (i.e., $dutchprof = 3$), there is no significant effect of $strongftr$ on their propensities to own financial wealth. Additionally, the null hypothesis of the Wald test 4 that $\beta_{FtrDutch} + \beta_{dutchprof} = 0$ cannot be rejected at the 10% significant level. This means that, for immigrants speaking strong-FTR home languages, there is no significant effect of (weak-FTR) Dutch proficiency on their propensities to own financial wealth.

In a word, using the sample of immigrants, we do not find the empirical evidence of the effect of a language's FTR on its speakers' propensities to own financial wealth. It could be that the quality of the data (e.g., $logincome$ and $dutchprof$) is not good enough and thus the regression results may fail to reveal the true pattern. For instance, the self-assessment rating of Dutch proficiency in the LISS panel may be inaccurate[8], especially with a scale of only three. Future research needs to use a more objective language placement test (Wu & Ortega, 2013) of Dutch proficiency for immigrants and more accurate information from administrative records on income and wealth from Statistics Netherlands.[9]

6 FTR and the amount of financial wealth of Dutch residents

This section tests hypotheses H3, H4 and H5 using the survey data. The previous binary variable $ownfin$ is not sensitive to the changes in the amount of the financial wealth. For instance, an individual with € 100,000 financial wealth and another individual with € 100 financial wealth are both classified as people who own financial wealth and have $ownfin = 1$. However, these two individuals are quite different from each other in the amount of financial wealth, which cannot be captured by variable $ownfin$. It would be interesting to

[8] A recent linguistic study reveals that a self-assessment rating of L2 English proficiency (5-point scaling) is uncorrelated with the outcome of an objective language placement test in the same sample (Gu, Hoetjes & Swerts, in preparation).

[9] In Appendix A, Table A.2 shows corresponding estimation results of binary choice models for the subsample of household heads of immigrants. The results are similar to those in Table 4. However, the results are likely to be biased (see Footnote 5). Future research is needed (see Footnote 7).

investigate the relationship between a language's FTR and the amount of financial wealth of its speakers. The dependent variable is a left-censored variable $logfin_{it}$ which equals to the log transformation of individual i's financial wealth if i owns positive financial wealth in wave t (otherwise equals 0). The analysis is conducted at the individual level with censored regression models for panel data, including static fixed-effects censored regression model, static random-effects tobit model, static quasi-fixed-effects tobit model, dynamic fixed-effects censored regression model, dynamic random-effects tobit model and dynamic quasi-fixed-effects tobit model. Both Stata 12 and Matlab 2012a will be used to do estimation.

6.1 Censored regression models for panel data

6.1.1 Static censored regression models for panel data

The basic setting of a static censored regression model is

$$\begin{aligned} logfin_{it}^{*} = \beta_0 &+ strongftr_i\beta_1 + dutchprof_{it}\beta_2 + logincome_{it}\beta_3 + female_i\beta_4 + age_i\beta_5 + edu_i\beta_6 \\ &+ west1_i\beta_7 + west2_i\beta_8 + nonwest1_i\beta_9 + nonwest2_i\beta_{10} + trust_{it}\beta_{11} + FtrDutch_{it}\beta_{12} \\ &+ househead_{it}\beta_{13} + \alpha_i + \epsilon_{it} \end{aligned}$$

$$FtrDutch_{it} = strongftr_i * dutchprof_{it}$$

$$logfin_{it} = max(0, logfin_{it}^{*})\ , t = 1,2,3$$

$$\begin{aligned} x_{it} = (1\ &strongftr_i\ dutchprof_{it}\ logincome_{it}\ trust_{it}\ \ female_i\ age_i\ edu_i\ west1_i\ west2_i\ nonwest1_i \\ &nonwest2_i\ FtrDutch_{it}\ househead_{it})' \end{aligned}$$

where α_i is an unobserved individual effect, x_{it} includes all explanatory variables, and $\beta's$ are coefficients to be estimated. The left-censored $logfin_{it}$ equals to the log transformation of i's financial wealth if i owns positive financial wealth in wave t, otherwise equals 0.

In a static fixed-effects censored regression model (Honoré, 1992), it is assumed that:

$$\alpha_i\text{: no assumption on } \alpha_i$$

$$\text{Conditional exchangeability: } (\epsilon_{it}, \epsilon_{is})|x_{i1}, x_{i2}, x_{i3}, \alpha_i \text{ has the same distribution as}$$
$$(\epsilon_{is}, \epsilon_{it})|x_{i1}, x_{i2}, x_{i3}, \alpha_i \text{ for all } s, t = 1,2,3$$

In a static random-effects tobit model, it is assumed that:

$$\epsilon_{it} \sim N(0, \sigma_\epsilon^2), \text{i.i.d.}, \text{independent of } (x_{i1}, x_{i2}, x_{i3})$$

$$\alpha_i \sim N(0, \sigma_\alpha^2), \text{independent of } (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}) \text{ and } (x_{i1}, x_{i2}, x_{i3})$$

In a static quasi-fixed-effects tobit model, it is assumed that:

$$\alpha_i = \delta avelogincome_i + \tilde{\alpha}_i$$

$$avelogincome_i \text{ is the mean over time of } logincome$$

$$\epsilon_{it} \sim N(0, \sigma_\epsilon^2), \text{i.i.d.}, \text{independent of } (x_{i1}, x_{i2}, x_{i3})$$

$$\tilde{\alpha}_i \sim N(0, \sigma_{\tilde{\alpha}}^2), \text{independent of } (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}) \text{ and } (x_{i1}, x_{i2}, x_{i3})$$

The coefficient β_k can be interpreted using the marginal effect of explanatory variable x_{itk}:

$$\frac{\partial E(logfin_{it}|x_{it}, \alpha_i)}{x_{itk}} = P(logfin_{it} > 0|x_{it}, \alpha_i) * \beta_k$$

The marginal effect can be calculated for an average observation, where $P(logfin_{it} > 0|x_{it}, \alpha_i)$ is replaced by its corresponding sample fraction 0.770[10].

The importance of unobserved heterogeneity is measured by

$$\rho = \frac{Var(\alpha_i)}{Var(\alpha_i) + Var(\epsilon_{it})}$$

6.1.2 Dynamic censored regression models for panel data

The basic setting of a dynamic censored regression model is

$$\begin{aligned} logfin_{it}^* = {} & \beta_0 + \gamma logfin_{i,t-1} + strongftr_i\beta_1 + dutchprof_{it}\beta_2 + logincome_{it}\beta_3 + female_i\beta_4 + age_i\beta_5 \\ & + edu_i\beta_6 + west1_i\beta_7 + west2_i\beta_8 + nonwest1_i\beta_9 + nonwest2_i\beta_{10} + trust_{it}\beta_{11} \\ & + FtrDutch_{it}\beta_{12} +ousehead_{it}\beta_{13} + \alpha_i + \epsilon_{it} \end{aligned}$$

$$FtrDutch_{it} = strongftr_i * dutchprof_{it}$$

$$logfin_{it} = \max(0, logfin_{it}^*), t = 2,3$$

$$\begin{aligned} x_{it} = {} & (1\ strongftr_i\ dutchprof_{it}\ logincome_{it}\ trust_{it}\ \ female_i\ age_i\ edu_i\ west1_i\ west2_i\ nonwest1_i \\ & nonwest2_i\ FtrDutch_{it}\ househead_{it})' \end{aligned}$$

where α_i is an unobserved individual effect and γ is a parameter of state dependence. The left-censored dependent variable $logfin_{it}$ equals to the log transformation of i's financial wealth if i owns positive financial wealth in wave t, otherwise equals 0.

[10] This sample fraction is obtained by pooling observations of all waves together.

In a dynamic random-effects tobit model using Wooldridge approach (Wooldridge, 2005), it is assumed that:

$$logfin_{i1} \text{ is treated as given}$$

$$\epsilon_{i2}, \epsilon_{i3}, N(0, \sigma_\epsilon^2), \text{i.i.d.}, \text{independent of } (x_{i2}, x_{i3}) \text{ and } logfin_{i1}$$

$$\alpha_i = \lambda logfin_{i1} + \tilde{\alpha}_i$$

$$\tilde{\alpha}_i \sim N\left(0, \sigma_{\tilde{\alpha}}^2\right), \text{independent of } (\epsilon_{i2}, \epsilon_{i3}), (x_{i2}, x_{i3}) \text{ and } logfin_{i1}$$

In a dynamic quasi-fixed-effects tobit model using Wooldridge approach (Wooldridge, 2005), it is assumed that:

$$logfin_{i1} \text{ is treated as given}$$

$$\epsilon_{i2}, \epsilon_{i3}, N(0, \sigma_\epsilon^2), \text{i.i.d.}, \text{independent of } (x_{i2}, x_{i3}) \text{ and } logfin_{i1}$$

$$\alpha_i = \lambda logfin_{i1} + \delta avelogincome_i + \tilde{\alpha}_i$$

$$avelogincome_i \text{ is the mean over time of } logincome$$

$$\tilde{\alpha}_i \sim N\left(0, \sigma_{\tilde{\alpha}}^2\right), \text{independent of } (\epsilon_{i2}, \epsilon_{i3}), (x_{i2}, x_{i3}) \text{ and } logfin_{i1}$$

In a dynamic fixed-effects censored regression model (Honoré, 1993), the setting of the model becomes

$$logfin_{it}^* = \gamma logfin_{i,t-1} + dutchprof_{it}\beta_2 + logincome_{it}\beta_3 + trust_{it}\beta_{11} + FtrDutch_{it}\beta_{12} + househead_{it}\beta_{13} + \alpha_i + \epsilon_{it}$$

$$FtrDutch_{it} = strongftr_i * dutchprof_{it}$$

$$logfin_{it} = \max(0, logfin_{it}^*), t = 2,3$$

$$x_{it} = (\, dutchprof_{it}\ logincome_{it}\ trust_{it}\ FtrDutch_{it}\ househead_{it})'$$

$$\beta = (\beta_2\ \beta_3\ \beta_{11}\ \beta_{12}\ \beta_{13})'$$

It is assumed that:

$$\alpha_i\text{: no assumption on } \alpha_i$$

$$\epsilon_{i2} \text{ and } \epsilon_{i3} \text{ have the same distribution given } y_{i1} \text{ and } \alpha_i$$

The corresponding moments are

$$E\left\{[max(-x_{i2}'\beta,-x_{i3}'\beta,logfin_{i3}-\gamma logfin_{i2}-x_{i3}'\beta)-max(-x_{i2}'\beta,-x_{i3}'\beta,logfin_{i2}-\gamma logfin_{i1} - x_{i2}'\beta)]\begin{pmatrix}1\\x_{i2}\\x_{i3}\\logfin_{i1}\end{pmatrix}\right\}=0$$

The calculation of the marginal effect of explanatory variable x_{itk} and the importance of unobserved heterogeneity is similar to that in static censored regression models.

6.2 A Monte Carlo study of the dynamic fixed-effects censored regression model

Since there is no available code of Stata 12 to estimate a dynamic fixed-effects censored regression model, a Matlab program is written using Matlab 2012a[11]. Suppose the basic setting of a simple dynamic fixed-effects censored regression model with three time periods for one individual is

$$y_{it}^{*}=\gamma y_{i,t-1}+x_{it1}\beta_1+x_{it2}\beta_2+\alpha_i+\epsilon_{it}, t=1,2$$

$$y_{it}=\max(0,y_{it}^{*}), t=1,2$$

$$x_{it}=(\,x_{it1}\;x_{it2}\,)'$$

$$\beta=(\beta_1\;\beta_2)'$$

This section will do a Monte Carlo study to investigate the validity of the Matlab program on dynamic fixed-effects censored regression model.

6.2.1 Data generating and moments

Following Honoré (1993), the data can be considered in an "ideal" situation in which all random variables are independently, normally distributed. Independent variables, individual effects, error terms and dependent variables are generated as follows:

$$x_{it2}, t=0,1,2\sim N(0,1), i.i.d.$$

$$\alpha_i \sim N(0,1), i.i.d., independent\ of\ x_{it2}$$

[11] The codes of dynamic fixed-effects censored regression model with three time periods are in Appendix B.

$$x_{it1} = \alpha_i + \eta_{it}, t = 0,1,2, where\ \eta_{it} \sim N(0,1), i.i.d., independent\ of\ \alpha_i$$

$$\epsilon_{it}, t = 0,1,2 \sim N(0,1), \text{i.i.d., independent of } (x_{it1}, x_{it2})\ and\ \alpha_i$$

$$y_{i0}^* = x_{i01}\beta_1 + x_{i02}\beta_2 + \alpha_i + \epsilon_{i0}$$

$$y_{it}^* = \gamma y_{i,t-1} + x_{it1}\beta_1 + x_{it2}\beta_2 + \alpha_i + \epsilon_{it}, t = 1,2$$

$$y_{it} = \max(0, y_{it}^*), t = 0,1,2$$

with the true values of parameters:

$$\begin{pmatrix} \gamma \\ \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} 0.3 \\ 1 \\ 0.7 \end{pmatrix}$$

The corresponding moments are

$$E\left\{[max(-x_{i1}'\beta, -x_{i2}'\beta, y_{i2} - \gamma y_{i1} - x_{i2}'\beta) - max(-x_{i1}'\beta, -x_{i2}'\beta, y_{i1} - \gamma y_{i0} - x_{i1}'\beta)]\begin{pmatrix} 1 \\ x_{i1} \\ x_{i2} \\ y_{i0} \end{pmatrix}\right\} = 0$$

6.2.2 Monte Carlo results

Table 5 shows Monte Carlo results of one-step GMM and two-step GMM[12], which are all based on 1000 repetitions. Almost all the standard deviations and the means of standard errors of one-step GMM are larger than those of two-step GMM, except for the means of standard errors of parameter γ. Furthermore, the standard deviations are more close to the means of standard errors when using two-step GMM. Thus the two-step GMM is used to do estimations in the following section 6.3, since two-step GMM gives more efficient estimations than one-step GMM.

Table 5 Monte Carlo results of dynamic fixed-effects censored regression model with three time periods

		One-step GMM			Two-step GMM		
	True value	Means	St.dev.	Means of st.err.	Means	St.dev.	Means of st.err.
γ	0.3	0.3023	0.0865	0.0417	0.2990	0.0541	0.0511
β_1	1	1.0046	0.0715	0.0753	1.0005	0.0581	0.0560
β_2	0.7	0.7055	0.0626	0.0672	0.7025	0.0538	0.0514

Notes: The number of individuals is 1000. The number of repetitions is 1000.

[12] The iterated GMM has also been tried. It gives very similar results as two-step GMM.

6.3 Results and discussions

Table 6 shows estimation results of censored regression models for the sample of Dutch natives and immigrants. The left-censored dependent variable $logfin_{it}$ equals to the log transformation of individual i's financial wealth if i owns positive financial wealth in wave t, otherwise equals 0. The Hausman test in column (2) helps to choose between static FE censored regression model and static RE tobit model. The null hypothesis (static RE tobit model) cannot be rejected at the 10% significant level, since t-value=-1.515>-1.64. Static QFE tobit model in column (3) allows the individual effect to depend upon the (individual specific) mean over time of $logincome$. The estimated coefficient of $avelogincome$ is significant at the 5% significant level. Thus the static QFE tobit model is preferred among static FE censored regression model, RE tobit and QFE tobit models.

Static QFE tobit model in column (4) further adds time dummies as additional independent variables. The Wald test 1 tests the joint significance of time dummies. The null of no relationship is rejected at the 5% significant level, since p-value=0.000<0.05. Thus time dummies should be added to static QFE tobit model.

Columns (5), (6) and (7) show estimation results of dynamic censored regression models. In column (7), the overidentification test shows that the null that the overidentifying restrictions are valid cannot be rejected at the 5% significant level, since p-value=0.769>0.05. The estimated coefficient of lag_logfin is not significant at the 5% significant level in all three columns, which means that there is no empirical evidence of state dependence. Thus the static QFE tobit model in column (4) is used for further analyses.

In column (4) of Table 6, the unobserved heterogeneity is significantly present. $\hat{\sigma}_{\tilde{\alpha}}$ is significant at the 1% significant level. The importance of unobserved heterogeneity is

$$\hat{\rho} = \frac{\widehat{Var}(\alpha_i)}{\widehat{Var}(\alpha_i) + \widehat{Var}(\epsilon_{it})} = \frac{\widehat{Var}(\delta avelogincome_i + \tilde{\alpha}_i)}{\widehat{Var}(\delta avelogincome_i + \tilde{\alpha}_i) + \widehat{Var}(\epsilon_{it})}$$

$$= \frac{\hat{\delta}^2 \widehat{Var}(avelogincome_i) + \hat{\sigma}_{\tilde{\alpha}}^2}{\hat{\delta}^2 \widehat{Var}(avelogincome_i) + \hat{\sigma}_{\tilde{\alpha}}^2 + \hat{\sigma}_{\epsilon}^2} = \frac{0.25^2 * 2^2 + 3.72^2}{0.25^2 * 2^2 + 3.72^2 + 3.09^2} \approx 0.596$$

The estimated coefficient of $strongftr$ is significantly negative at the 1% significant level. The corresponding marginal effect is

$$\hat{P}(logfin_{it} > 0 | x_{it}, \alpha_i) * \hat{\beta}_{strongftr} = 0.770 * (-1.815) \approx -1.398$$

This means for an average person, if his/her home language changes from a strong-FTR language to a weak-FTR language, then his/her financial wealth is expected to increase by 139.8%, keeping other variables unchanged. The effect of $strongftr$ on the amount of financial wealth is negative, which is in line with Chen's linguistic-saving theory.[13]

Four origin dummies ($west1$, $west2$, $nonwest1$ and $nonwest2$) are again used to account for the potential non-linguistic cultural factors of four different immigrants groups. Alternatively, three origin dummies can be constructed: $west$ ((1, 0) if the individual has a western background), $gene1$ ((1, 0) if being a first generation immigrant) and $gene2$ ((1, 0) if being a second generation immigrant). The former way of four origin dummies allows the interaction between background and generation whereas the latter way of three origin dummies does not. Wald test 2 helps to make clear whether there is an interaction between background and generation. The null hypothesis that $\beta_{west2} - \beta_{west1} = \beta_{nonwest2} - \beta_{nonwest1}$ cannot be rejected at the 5% significant level, since p-value is larger than 0.05. There is not enough evidence to conclude that the difference in the amount of financial wealth between first generation and second generation immigrants with western background is different from the difference in the amount of financial wealth between first generation and second generation immigrants with non-western background, keeping other variables unchanged. In other words, there is not enough evidence to conclude that the difference in the amount of financial wealth between western and non-western first-generation immigrants is different from the difference in the amount of financial wealth between western and non-western second-generation immigrants, keeping other variables unchanged.

[13] In Appendix A, Table A.3 shows corresponding estimation results of censored regression models for the subsample of household heads of Dutch natives and immigrants. The estimated coefficient of $strongftr$ becomes less significant in columns (2), (3) and (4) than that in Table 6. In column (4) of Table A.3, the estimated coefficient of $strongftr$ is significant only at the 15% significant level. However, the results are likely to be biased (see Footnote 5). Future research is needed (see Footnote 7).

Table 6 FTR and the amount of financial wealth: sample of Dutch natives and immigrants

	Static censored regression models				Dynamic censored regression models		
	(1) FE	(2) RE	(3) QFE	(4) QFE	(5) QFE	(6) RE	(7) FE
Strongftr		-1.920***	-1.866***	-1.815***	-1.225*	-1.226*	
		(0.633)	(0.634)	(0.631)	(0.647)	(0.646)	
Lag_logfin					0.000783	0.00407	-0.0040
					(0.0434)	(0.0414)	(0.0693)
Logfin_0					0.559***	0.557***	
					(0.0403)	(0.0390)	
Logincome	0.146**	0.232***	0.114**	0.0424	0.115	0.118***	0.118
	(0.0657)	(0.0331)	(0.0561)	(0.0555)	(0.0784)	(0.0388)	(0.112)
Avelogincome			0.177***	0.249***	0.00364		
			(0.0683)	(0.0677)	(0.0879)		
Female		-1.042***	-1.002***	-1.029***	-0.436**	-0.435**	
		(0.169)	(0.170)	(0.169)	(0.171)	(0.170)	
Age		0.0311***	0.0292***	0.0271***	0.0107**	0.0108**	
		(0.00487)	(0.00492)	(0.00490)	(0.00495)	(0.00487)	
Edu		0.761***	0.741***	0.744***	0.210***	0.210***	
		(0.0527)	(0.0533)	(0.0530)	(0.0558)	(0.0553)	
Trust	0.0411	0.184***	0.186***	0.162***	0.104***	0.104***	-0.0459
	(0.0451)	(0.0298)	(0.0298)	(0.0296)	(0.0358)	(0.0358)	(0.0783)
Househead	-0.306	-0.000533	-0.0400	-0.144	-0.212	-0.210	-0.408
	(0.288)	(0.178)	(0.179)	(0.178)	(0.192)	(0.191)	(1.082)
Constant		0.390	0.161	0.940**	1.149***	1.130***	
		(0.395)	(0.405)	(0.409)	(0.443)	(0.431)	
Origin dummies	No	Yes	Yes	Yes	Yes	Yes	No
Househead*Origin dummies	Yes	Yes	Yes	Yes	Yes	Yes	No
Time dummies	No	No	No	Yes	Yes	No	No
$\hat{\sigma}_{\alpha}$		3.724***					
		(0.0736)					
$\hat{\sigma}_{\tilde{\alpha}}$			3.725***	3.721***	2.266***	2.259***	
			(0.0735)	(0.0727)	(0.139)	(0.136)	
$\hat{\sigma}_{\epsilon}$		3.151***	3.149***	3.090***	2.744***	2.748***	
		(0.0434)	(0.0433)	(0.0426)	(0.0847)	(0.0831)	
Hausman test (t-value)		-1.515					
Wald test 1 (p-value)				0.000	0.809		
Wald test 2 (p-value)				0.673			
Overidentification test (p-value)							0.769
Log likelihood		-18288.86	-18285.498	-18198.934	-7449.373	-7449.402	
Observations	7,336	7,336	7,336	7,336	3,107	3,107	3,057
Individuals	3767	3,767	3,767	3,767	1,890	1,890	1019

Notes: Data source: LISS panel, sample of Dutch natives and immigrants. The dependent variable is a left-censored variable $logfin_{it}$ which equals to the log transformation of individual i's financial wealth if i owns positive financial wealth in wave t (otherwise equals 0). $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. "Househead*Origin dummies" means interaction terms between $househead$ and origin dummies ($west1$, $west2$, $nonwest1$ and $nonwest2$). As for the Hausman test in column (2), H0: RE model, H1: FE model. It looks at coefficient of $logincome$ only. The Wald test 1 tests the joint significance of time dummies. As for the Wald test 2, H0: $\beta_{west2} - \beta_{west1} = \beta_{nonwest2} - \beta_{nonwest1}$. As for the overidentification test, H0: the overidentifying restrictions are valid. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

To investigate the effect of Dutch proficiency on the amount of financial wealth of immigrants and to test hypotheses H4 and H5, Table 7 further adds $dutchprof$ and $FtrDutch$ (i.e., the interaction between $strongftr$ and $dutchprof$) as independent variables and use the sample of immigrants only. The left-censored dependent variable is still $logfin_{it}$, which equals to the log transformation of individual i's financial wealth if i owns positive financial wealth in wave t (otherwise equals 0). The Hausman test in column (2) helps to choose between static FE censored regression model and static RE tobit model. The null hypothesis (static RE tobit model) cannot be rejected at the 5% significant level, since t-value=-0.922>-1.96. Static QFE tobit model in column (3) allows the individual effect to depend upon the (individual specific) mean over time of $logincome$. The estimated coefficient of $avelogincome$ is not significant at the 10% significant level. Thus the static RE tobit model is preferred among static FE censored regression model, RE tobit and QFE tobit models.

Static RE tobit model in column (4) further adds time dummies as additional independent variables. The Wald test 1 tests the joint significance of time dummies. The null of no relationship is rejected at the 5% significant level, since p-value=0.000<0.05. Thus time dummies should be added to static RE tobit model.

Columns (5), (6) and (7) show estimation results of dynamic censored regression models. The estimated coefficient of lag_logfin is significant at the 10% (or even 1%) significant level in all three columns, and hence the dynamic censored regression models are preferred to the static censored regression models.

In column (7), the overidentification test shows that the null that the overidentifying restrictions are valid cannot be rejected at the 5% significant level, since p-value=0.296>0.05. The Hausman test in column (6) helps to choose between dynamic FE censored regression model and dynamic RE tobit model. The null hypothesis (dynamic RE tobit model) cannot be rejected at the 5% significant level, since t-value=0.0463<1.96. Dynamic QFE tobit model in column (5) adds time dummies as independent variables and allows the individual effect to depend upon the (individual specific) mean over time of $logincome$. The estimated coefficients of $avelogincome$ and the time dummy are not significant at the 10% significant level. Thus the dynamic RE tobit model is preferred among dynamic FE censored regression model, RE tobit and QFE tobit models.

Table 7 FTR and the amount of financial wealth: sample of immigrants

	Static censored regression models				Dynamic censored regression models		
	(1) FE	(2) RE	(3) QFE	(4) RE	(5) QFE	(6) RE	(7) FE
Strongftr		1.188	1.442	2.760	4.930	4.775	
		(3.395)	(3.394)	(3.331)	(3.209)	(3.250)	
FtrDutch	0.0930	-1.206	-1.269	-1.779	-2.218*	-2.182*	-0.617
	(2.969)	(1.264)	(1.263)	(1.240)	(1.190)	(1.208)	(3.471)
Dutchprof	-0.693	0.722	0.738	1.024	0.361	0.285	-2.775
	(1.679)	(0.918)	(0.917)	(0.898)	(0.803)	(0.817)	(3.196)
Lag_logfin					0.461***	0.374*	0.255**
					(0.0895)	(0.210)	(0.110)
Logfin_0					0.163*	0.228	
					(0.0855)	(0.172)	
Logincome	-0.0527	0.132	-0.146	0.105	0.148	0.359***	0.426
	(0.232)	(0.117)	(0.210)	(0.115)	(0.351)	(0.118)	(1.453)
Avelogincome			0.402		0.249		
			(0.253)		(0.383)		
Female		-0.0822	-0.0112	-0.259	-0.470	-0.487	
		(0.604)	(0.605)	(0.600)	(0.476)	(0.488)	
Age		0.0335*	0.0292	0.0268	0.0157	0.0181	
		(0.0192)	(0.0194)	(0.0191)	(0.0153)	(0.0157)	
Edu		0.677***	0.655***	0.691***	0.220	0.243	
		(0.176)	(0.176)	(0.175)	(0.144)	(0.149)	
Trust	0.179	0.279***	0.282***	0.251***	0.250**	0.249**	0.164
	(0.142)	(0.0988)	(0.0986)	(0.0960)	(0.107)	(0.108)	(0.186)
Househead	5.051	1.647	1.447	1.568	-0.618	-0.489	-2.151
	(3.701)	(1.659)	(1.663)	(1.634)	(1.603)	(1.619)	(2.079)
Constant		-5.004*	-5.515*	-4.100	-4.272	-3.791	
		(3.030)	(3.044)	(2.990)	(2.729)	(2.756)	
Origin dummies	No	Yes	Yes	Yes	Yes	Yes	No
Househead*Origin dummies	Yes	Yes	Yes	Yes	Yes	Yes	No
Time dummies	No	No	No	Yes	Yes	No	No
$\hat{\sigma}_{\alpha}$		4.294***		4.344***			
		(0.287)		(0.279)			
$\hat{\sigma}_{\tilde{\alpha}}$			4.288***		1.14E-06	0.977	
			(0.286)		(2.446)	(1.606)	
$\hat{\sigma}_{\epsilon}$		3.704***	3.698***	3.504***	3.457***	3.329***	
		(0.173)	(0.173)	(0.164)	(0.163)	(0.472)	
Hausman test (t-value)		-0.922				0.0463	
Wald test 1 (p-value)				0.000	0.334		
Wald test 2 (p-value)						0.213	
Wald test 3 (p-value)						0.0254	
Wald test 4 (p-value)						0.0356	
Overidentification test (p-value)							0.296
Log likelihood		-1813.385	-1812.115	-1792.128	-748.283	-748.949	
Observations	792	792	792	792	331	331	336
Individuals	416	416	416	416	208	208	112

Notes: Data source: LISS panel, sample of immigrants. The dependent variable is a left-censored variable $logfin_{it}$ which equals to the log transformation of individual i's financial wealth if i owns positive financial wealth in wave t (otherwise equals 0). $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. $Dutchprof$ (i.e., Dutch proficiency) ranges from 1 (low level) to 3 (high level). "Househead*Origin dummies" means interaction terms between $househead$ and origin dummies ($west1$, $west2$, $nonwest1$ and $nonwest2$). As for the Hausman test in columns (2) and (6), H0: RE model, H1: FE model. Both tests look at coefficient of $logincome$ only. The Wald test 1 tests the joint significance of time dummies. As for the Wald test 2, H0: $\beta_{strongftr} + \beta_{FtrDutch} = 0$. As for the Wald test 3, H0: $\beta_{strongftr} + 3\beta_{FtrDutch} = 0$. As for the Wald test 4, H0: $\beta_{FtrDutch} + \beta_{dutchprof} = 0$. As for the overidentification test, H0: the overidentifying restrictions are valid. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In column (6) of Table 7, the estimated coefficient of lag_logfin is significant at the 10% significant level, which means that there is empirical evidence of (positive) state dependence. The estimated coefficient of $logfin\_0$ is not significant at the 10% significant level, so the null hypothesis of no correlation between individual effects and the initial value of $logfin$ cannot be rejected. Furthermore, $\hat{\sigma}_{\tilde{\alpha}}$ is not significant at the 10% significant level. A pooled tobit regression is also tried. It is assumed that there is no individual effect (unobserved heterogeneity) and lag_logfin is included as an exogenous independent variable. The results are similar to those in column (6).

In column (6), the null hypothesis of the Wald test 3 that $\beta_{strongftr} + 3\beta_{FtrDutch} = 0$ is rejected at the 5% significant level, and $\hat{\beta}_{strongftr} + 3\hat{\beta}_{FtrDutch} < 0$. This means that, for immigrants with the high level of Dutch proficiency (i.e., $dutchprof = 3$), there is a significant negative effect of $strongftr$ on the amount of financial wealth, which is in line with Chen's linguistic-saving theory. Given the fact that a foreign language can also influence one's thinking (bilingual-minds theory), a high Dutch proficiency should have moderated the effect of $strongftr$. Then one possible explanation for the result can be that an immigrant's home language is persistently dominant even when the level of (host-country language) Dutch proficiency is high. If so, then it is expected that there also exists such a negative effect of $strongftr$ on the amount of financial wealth for immigrants with the low level of Dutch proficiency. Moreover, the negative effect may be stronger as the low level of Dutch proficiency is less likely to moderate the $strongftr$ effect.

Surprisingly, the null hypothesis of the Wald test 2 that $\beta_{strongftr} + \beta_{FtrDutch} = 0$ cannot be rejected at the 10% significant level. This means that, for immigrants with the low level of Dutch proficiency (i.e., $dutchprof = 1$), $strongftr$ has no significant correlation with the amount of financial wealth. Nevertheless, given there are only five observations from two individuals whose Dutch proficiency is low, the results are not reliable.

Additionally, the null hypothesis of the Wald test 4 that $\beta_{FtrDutch} + \beta_{dutchprof} = 0$ is rejected at the 5% significant level, and $\hat{\beta}_{FtrDutch} + \hat{\beta}_{dutchprof} < 0$. For immigrants speaking strong-FTR home languages, $dutchprof$ is negatively correlated with the amount of financial wealth. This is inconsistent with Chen's linguistic-saving theory and the hypothesis H4. However, it could be that the quality of the data (e.g., $logfin$,

$logincome$ and $dutchprof$) is not good enough and thus the regression results may fail to reveal the true pattern. For instance, the self-assessment rating of Dutch proficiency in the LISS panel is inaccurate and there are too many missing values on the amount of financial wealth in the data. More research in the future is needed.[14]

7 Conclusions

This paper empirically studies the effect of one aspect of language structure, future-time-reference (FTR), on retirement planning and financial wealth using the Dutch sample. First of all, the study with the sample of Dutch natives and immigrants finds that immigrants who speak strong-FTR home languages have thought less about their retirement, are less likely to own and own less financial wealth than native Dutch and immigrants speaking weak-FTR home languages. These findings are largely consistent with Chen (2013)'s linguistic-savings theory that languages with obligatory future-time-reference (i.e., strong-FTR languages) lead their speakers to save less.

Furthermore, based on the sample of immigrants, for immigrants who speak strong-FTR home languages, there is a significant positive effect of (weak-FTR) Dutch proficiency on their retirement planning. In contrast, for immigrants who speak weak-FTR home languages, the effect of Dutch proficiency is not significant. Additionally, for immigrants with low Dutch proficiency, there is a significant negative effect of $strongftr$ on their retirement planning, whereas for immigrants with high Dutch proficiency, there is no significant effect of $strongftr$ on their retirement planning. The difference in retirement planning between Dutch proficiency levels is due to the host-country language Dutch but not Dutch culture (see section 4.2). The results provide empirical evidence for the bilingual-minds theory, which claims that home and host-country languages of immigrants are co-activated and there are bi-directional influences between different languages.

The above findings have implications for the policy related to pension, e.g., targeting of pension communication to specific groups which becomes more relevant with current ongoing pension reforms that

[14] In Appendix A, Table A.4 shows corresponding estimation results of censored regression models for the subsample of household heads of immigrants. The results do not provide empirical evidence for the effect of a language's FTR on the amount of financial wealth. However, the results are likely to be biased (see Footnote 5). Future research is needed (see Footnote 7).

put more responsibility with the individuals themselves. The results call for some extra communication and help for immigrants, who speak strong-FTR home languages and are less proficient in Dutch, to make them more aware of the importance of pension planning.

However, the study of the sample of immigrants does not provide strong evidence for the effect of $strongftr$ and the weak-FTR host-country language (Dutch) on the financial wealth of immigrants in the Netherlands. The empirical results are partially inconsistent with Chen's linguistic-savings theory. Perhaps the quality of the data (e.g., $logfin$, $logincome$ and $dutchprof$) is not good enough and hence needs more data to analyze in the future. The information in the LISS panel will be further expanded with an objective language placement test (Wu & Ortega, 2013) of Dutch proficiency for immigrants and with the information from administrative records on assets and wealth from Statistics Netherlands. Furthermore, possible return migration should be taken into account, which will influence pension plans. Direct information on return intentions is unavailable in LISS panel, but can be collected. Additionally, information on financial literacy needs to be collected as well. In a word, more sound data will be used to further test the hypotheses.

Furthermore, it is likely that the linguistic effect on the financial wealth is originated from the culture. For instance, in the Dutch culture being thrifty is highly appreciated, and Dutch is a weak-FTR language which also encourages more savings and financial wealth. It could be that immigrants with higher Dutch proficiency get more access to all the Dutch information and are more influenced by the Dutch culture. In this sense, the culture can be a potential confounding factor for the effect of Dutch proficiency on the financial wealth of immigrants. It would be interesting to further investigate whether the effect of language structure FTR on financial wealth is still significant after controlling for culture related factors. Future study can (1) control for individual cultural values, such as whether saving is considered important and thriftiness is appreciated, or alternatively (2) control for the culture at the country level for immigrants by referring to Hofstede's six cultural dimensions (Hofstede, 2010) and add the years of residence in the Netherlands as an additional independent variable. This will provide us a better understanding of whether language is a proxy of non-linguistic culture or itself can also lead to different individual behavior.

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Appendix A: Regression results of subsample of household heads only

Table A.1 FTR and the propensity to own financial wealth: subsample of household heads of Dutch natives and immigrants

	Static logit models				Dynamic logit models	
	(1) FE	(2) RE	(3) QFE	(4) QFE	(5) QFE	(6) RE
Strongftr		-0.434	-0.394	-0.388	0.618	0.613
		(0.474)	(0.476)	(0.510)	(0.628)	(0.650)
Lag_ownfin					0.496	0.320
					(0.395)	(0.353)
Ownfin_0					2.053***	2.247***
					(0.502)	(0.474)
Logincome	-0.149	0.159***	-0.0488	-0.0482	-0.00200	0.127
	(0.115)	(0.0575)	(0.0960)	(0.101)	(0.138)	(0.0802)
Avelogincome			0.294***	0.329***	0.171	
			(0.108)	(0.114)	(0.152)	
Female		-0.320**	-0.261*	-0.292*	0.178	0.140
		(0.153)	(0.155)	(0.165)	(0.209)	(0.212)
Age		-0.00286	-0.00482	-0.00577	0.00747	0.00903
		(0.00512)	(0.00517)	(0.00551)	(0.00702)	(0.00715)
Edu		0.492***	0.479***	0.509***	0.336***	0.353***
		(0.0523)	(0.0525)	(0.0564)	(0.0754)	(0.0766)
Trust	0.0696	0.119***	0.120***	0.112***	0.110***	0.111***
	(0.0446)	(0.0288)	(0.0289)	(0.0308)	(0.0411)	(0.0421)
West1		-0.972**	-0.986**	-1.066**	-0.549	-0.547
		(0.418)	(0.419)	(0.448)	(0.564)	(0.584)
West2		-0.323	-0.328	-0.367	-0.444	-0.443
		(0.333)	(0.333)	(0.354)	(0.416)	(0.430)
Nonwest1		-1.876***	-1.922***	-2.067***	-1.290**	-1.312**
		(0.409)	(0.411)	(0.442)	(0.528)	(0.543)
Nonwest2		-0.807	-0.829	-0.758	0.823	0.881
		(0.664)	(0.667)	(0.710)	(1.388)	(1.412)
Constant		0.152	-0.331	0.0726	-1.947***	-1.595**
		(0.541)	(0.561)	(0.605)	(0.748)	(0.742)
Time dumies	No	No	No	Yes	Yes	No
$\hat{\sigma}_{\alpha}$		1.770***				
		(0.137)				
$\hat{\sigma}_{\tilde{\alpha}}$			1.777***	1.956***	1.415***	1.527***
			(0.137)	(0.150)	(0.382)	(0.346)
Hausman test (p-value)		0.0018	0.0673			
Wald test 1 (p-value)				0.000	0.348	
Wald test 2 (p-value)				0.516		
Log likelihood	-310.324	-1649.747	-1646.153	-1591.928	-693.367	-694.474
Observations	862	5,966	5,966	5,966	3,407	3,407
Individuals	316	2,659	2,659	2,659	2,027	2,027

Notes: Data source: LISS panel, subsample of household heads of Dutch natives and immigrants. The dependent variable is a binary variable $ownfin_{it}$ which equals to 1 if individual i owns financial wealth in wave t. $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. As for the Hausman test in column (2), H0: RE model, H1: FE model. As for the Hausman test in column (3), H0: QFE model, H1: FE model. Both tests look at coefficients of all time-varying variables. The Wald test 1 tests the joint significance of time dummies. As for the Wald test 2, H0: $\beta_{west2} - \beta_{west1} = \beta_{nonwest2} - \beta_{nonwest1}$. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.2 FTR and the propensity to own financial wealth: subsample of household heads of immigrants

	Static logit models				Dynamic logit models	
	(1) FE	(2) RE	(3) QFE	(4) QFE	(5) QFE	(6) RE
Strongftr		-3.845	-3.741	-3.802	0.834	0.949
		(2.873)	(2.872)	(3.086)	(3.621)	(3.718)
FtrDuctch	34.95	1.427	1.425	1.441	0.455	0.391
	(5,339)	(1.070)	(1.071)	(1.150)	(1.401)	(1.436)
Dutchprof	-34.66	-0.225	-0.261	-0.342	1.324	1.462
	(5,339)	(0.779)	(0.779)	(0.835)	(0.982)	(1.004)
Lag_ownfin					0.992	0.826
					(0.935)	(0.819)
Ownfin_0					2.410*	2.707**
					(1.400)	(1.324)
Logincome	0.117	0.405**	-0.0449	0.00758	-0.00264	0.450**
	(0.302)	(0.179)	(0.291)	(0.313)	(0.432)	(0.226)
Avelogincome			0.759*	0.763*	0.742	
			(0.388)	(0.413)	(0.672)	
Female		-0.423	-0.270	-0.310	0.0415	-0.0867
		(0.449)	(0.454)	(0.484)	(0.623)	(0.628)
Age		0.0156	0.0111	0.00693	0.0340	0.0368
		(0.0166)	(0.0167)	(0.0177)	(0.0227)	(0.0235)
Edu		0.323**	0.311**	0.321**	0.406*	0.431**
		(0.138)	(0.138)	(0.148)	(0.215)	(0.213)
Trust	0.176	0.0869	0.0757	0.0788	0.0585	0.0697
	(0.142)	(0.0820)	(0.0820)	(0.0885)	(0.123)	(0.126)
Constant		-1.800	-3.678	-2.815	-9.266**	-8.352**
		(2.688)	(2.825)	(2.990)	(4.224)	(3.874)
Origin dummies	No	Yes	Yes	Yes	Yes	Yes
Time dumies	No	No	No	Yes	Yes	No
$\hat{\sigma}_{\alpha}$		2.128***				
		(0.431)				
$\hat{\sigma}_{\tilde{\alpha}}$			2.111***	2.299***	1.490	1.611*
			(0.434)	(0.475)	(1.010)	(0.905)
Hausman test (p-value)		0.995				
Wald test 1 (p-value)				0.001	0.512	
Wald test 2 (p-value)				0.233		
Wald test 3 (p-value)				0.515		
Wald test 4 (p-value)				0.149		
Log likelihood	-36.241	-241.047	-239.027	-230.231	-87.492	-88.324
Observations	113	625	625	625	355	355
Individuals	41	284	284	284	208	208

Notes: Data source: LISS panel, subsample of household heads of immigrants. The dependent variable is a binary variable $ownfin_{it}$ which equals to 1 if individual i owns financial wealth in wave t. $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. $Dutchprof$ (i.e., Dutch proficiency) ranges from 1 (low level) to 3 (high level). As for the Hausman test in column (2), H0: RE model, H1: FE model. It looks at the coefficients of all time-varying variables. The Wald test 1 tests the joint significance of time dummies. As for the Wald test 2, H0: $\beta_{strongftr} + \beta_{FtrDutch} = 0$. As for the Wald test 3, H0: $\beta_{strongftr} + 3\beta_{FtrDutch} = 0$. As for the Wald test 4, H0: $\beta_{FtrDutch} + \beta_{dutchprof} = 0$. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.3 FTR and the amount of financial wealth: subsample of household heads of Dutch natives and immigrants

	Static censored regression models				Dynamic censored regression models		
	(1) FE	(2) RE	(3) QFE	(4) QFE	(5) QFE	(6) QFE	(7) FE
Strongftr		-1.500*	-1.413*	-1.343†	-0.846	-0.850	
		(0.823)	(0.823)	(0.818)	(0.827)	(0.824)	
Lag_logfin					0.0102	0.0190	-0.0145
					(0.0529)	(0.0516)	(0.0708)
Logfin_0					0.559***	0.552***	
					(0.0497)	(0.0489)	
Logincome	-0.0265	0.276***	0.0578	0.0497	-0.134	-0.129	-0.207
	(0.0940)	(0.0747)	(0.0987)	(0.0978)	(0.126)	(0.127)	(0.150)
Avelogincome			0.436***	0.464***	0.396**	0.390**	
			(0.130)	(0.130)	(0.171)	(0.171)	
Female		-0.855***	-0.751***	-0.744***	-0.320	-0.317	
		(0.204)	(0.206)	(0.205)	(0.200)	(0.199)	
Age		0.0553***	0.0507***	0.0496***	0.0248***	0.0247***	
		(0.00642)	(0.00655)	(0.00651)	(0.00652)	(0.00650)	
Edu		0.883***	0.844***	0.846***	0.281***	0.280***	
		(0.0634)	(0.0643)	(0.0640)	(0.0654)	(0.0652)	
Trust	0.0528	0.224***	0.226***	0.205***	0.154***	0.153***	-0.0434
	(0.0526)	(0.0355)	(0.0354)	(0.0353)	(0.0411)	(0.0410)	(0.0757)
Constant		-1.893***	-3.137***	-2.770***	-1.542*	-1.579*	
		(0.692)	(0.785)	(0.782)	(0.879)	(0.874)	
Origin dummies	No	Yes	Yes	Yes	Yes	Yes	No
Time dummies	No	No	No	Yes	Yes	No	No
$\hat{\sigma}_{\alpha}$		3.572***					
		(0.0881)					
$\hat{\sigma}_{\tilde{\alpha}}$			3.569***	3.553***	2.131***	2.112***	
			(0.0878)	(0.0871)	(0.158)	(0.158)	
$\hat{\sigma}_{\epsilon}$		2.788***	2.783***	2.752***	2.419***	2.430***	
		(0.0498)	(0.0497)	(0.0492)	(0.0972)	(0.0968)	
Hausman test (t-value)		-5.301					
Wald test 1 (p-value)				0.000	0.551		
Wald test 2 (p-value)				0.0234			
Overidentification test (p-value)							0.832
Log likelihood		-10432.839	-10427.23	-10390.549	-4272.270	-4272.447	
Observations	4,192	4,192	4,192	4,192	1,824	1,824	1851
Individuals	2,135	2,135	2,135	2,135	1,100	1,100	617

Notes: Data source: LISS panel, subsample of household heads of Dutch natives and immigrants. The dependent variable is a left-censored variable $logfin_{it}$ which equals to the log transformation of individual i's financial wealth if i owns positive financial wealth in wave t (otherwise equals 0). $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. As for the Hausman test in column (2), H0: RE model, H1: FE model. It looks at coefficient of $logincome$ only. The Wald test 1 tests the joint significance of time dummies. As for the Wald test 2, H0: $\beta_{west2} - \beta_{west1} = \beta_{nonwest2} - \beta_{nonwest1}$. As for the overidentification test, H0: the overidentifying restrictions are valid. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1, † p<0.15

Table A.4 FTR and the amount of financial wealth: subsample of household heads of immigrants

	Static censored regression models				Dynamic censored regression models		
	(1) FE	(2) RE	(3) QFE	(4) QFE	(5) QFE	(6) RE	(7) FE
Strongftr		-2.158	-2.250	-0.224	2.642	2.035	
		(4.718)	(4.690)	(4.621)	(5.244)	(5.158)	
FtrDuctch	4.261**	0.195	0.319	-0.398	-1.065	-0.913	0.896
	(2.104)	(1.777)	(1.768)	(1.741)	(1.907)	(1.881)	(7.034)
Dutchprof	-2.422*	-0.116	-0.239	0.231	0.403	0.485	-1.873
	(1.360)	(1.220)	(1.214)	(1.195)	(1.263)	(1.250)	(4.429)
Lag_logfin					0.167	0.228	0.0639
					(0.187)	(0.196)	(0.169)
Logfin_0					0.443**	0.418**	
					(0.173)	(0.180)	
Logincome	0.0636	0.733**	-0.168	-0.120	-1.387	0.365	-5.050
	(0.190)	(0.359)	(0.533)	(0.522)	(1.440)	(0.358)	(3.710)
Avelogincome			1.780**	1.756**	2.503		
			(0.777)	(0.769)	(2.011)		
Female		-0.102	0.344	0.227	-0.441	-0.522	
		(0.807)	(0.823)	(0.818)	(0.712)	(0.696)	
Age		0.0668**	0.0568*	0.0496*	0.0226	0.0227	
		(0.0291)	(0.0291)	(0.0289)	(0.0252)	(0.0249)	
Edu		0.628***	0.574**	0.572**	0.0443	0.105	
		(0.235)	(0.233)	(0.232)	(0.213)	(0.203)	
Trust	0.270**	0.307**	0.287**	0.256**	0.281**	0.296**	0.222
	(0.121)	(0.130)	(0.129)	(0.127)	(0.136)	(0.136)	(0.182)
Constant		-6.617	-12.10**	-12.11**	-9.041	-4.581	
		(4.615)	(5.239)	(5.169)	(6.113)	(4.632)	
Origin dummies	No	Yes	Yes	Yes	Yes	Yes	No
Time dummies	No	No	No	Yes	Yes	No	No
$\hat{\sigma}_{\alpha}$		4.629***					
		(0.383)					
$\hat{\sigma}_{\tilde{\alpha}}$			4.576***	4.569***	2.377***	2.252***	
			(0.380)	(0.373)	(0.619)	(0.681)	
$\hat{\sigma}_{\epsilon}$		3.376***	3.364***	3.258***	2.691***	2.783***	
		(0.204)	(0.203)	(0.197)	(0.367)	(0.393)	
Wald test 1 (p-value)				0.000	0.489		
Wald test 2 (p-value)				0.834			
Wald test 3 (p-value)				0.313			
Wald test 4 (p-value)				0.895			
Overidentification test (p-value)							0.876
Log likelihood		-1035.242	-1032.410	-1024.373	-447.415	-448.395	
Observations	456	446	446	446	201	201	219
individuals	230	226	226	226	121	121	73

Notes: Data source: LISS panel, subsample of household heads of immigrants. The dependent variable is a left-censored variable $logfin_{it}$ which equals to the log transformation of individual i's financial wealth if i owns positive financial wealth in wave t (otherwise equals 0). $Strongftr$ is a binary variable, which equals to 1 if the individual speaks a strong-FTR home language. $Dutchprof$ (i.e., Dutch proficiency) ranges from 1 (low level) to 3 (high level). The Wald test 1 tests the joint significance of time dummies. As for the Wald test 2, H0: $\beta_{strongftr} + \beta_{FtrDutch} = 0$. As for the Wald test 3, H0: $\beta_{strongftr} + 3\beta_{FtrDutch} = 0$. As for the Wald test 4, H0: $\beta_{FtrDutch} + \beta_{dutchprof} = 0$. As for the overidentification test, H0: the overidentifying restrictions are valid. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix B: Matlab codes of the dynamic fixed-effects censored regression model

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function output=dyFEcenmoment(par,condition,y0,y1,y2,x1,x2,W)
% This function defines moment conditions and objective function for dynamic
% FE censored regression model with three time periods.
%
% Input:
%               par: parameter values.
%                y0: dependent variable in the first time period, a N*1 vector
%                    where N is the number of individuals in the sample.
%                y1: dependent variable in the second time period, a N*1 vector
%                    where N is the number of individuals in the sample.
%                y2: dependent variable in the third time period, a N*1 vector
%                    where N is the number of individuals in the sample.
%                x1: exogenous independent variables in the second time period, a
%                    N*k matrix where k is the number of exogenous independent
%                    variables.
%                x2: exogenous independent variables in the third time period, a
%                    N*k matrix where k is the number of exogenous independent
%                    variables.
%                 W: weight matrix, a R*R matrix where R is the number of moment
%                    conditions.
%         condition: if condition=1, then the output is the value of objective
%                    function of GMM, a scalar.
%                    if condition=2, then the output is a N*R moment-condition
%                    matrix where R is the number of moment conditions for every
%                    individual;
%                    if condition=3, then the output is the sample mean of moment
%                    conditions, a R*1 vector;
%
% Output:
%            output: depends on the value of condition.

% number of individuals in the sample
N=size(x1,1);
% number of moment conditions for every indivudal
R=2*size(x1,2)+2;

momenti=NaN(N,R);

gamma=par(1);
beta=par(2:end);
```

```
eta1=y1-gamma*y0-x1*beta;
eta2=y2-gamma*y1-x2*beta;

for i=1:N
    a1=[-x1(i,:)*beta,-x2(i,:)*beta,eta1(i,:)];
    a2=[-x1(i,:)*beta,-x2(i,:)*beta,eta2(i,:)];
    a=max(a2)-max(a1);
    momenti(i,:)=a*[1,x1(i,:),x2(i,:),y0(i,:)];
end

momentbar=mean(momenti)';
objfun=momentbar'*W*momentbar;

if condition==1
    output=objfun;
elseif condition==2
    output=momenti;
elseif condition==3
    output=momentbar;
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [parameter,stdErr,iterationnum,pvalue,chisquarevalue,chiPvalue]=...
    gmmonestep(momentconditions,y0,y1,y2,x1,x2,startingvalues)
% This function is for one-step GMM estimation for dynamic panel data model
% with three time periods.
%
% Input:
%     momentconditions: a fuction for moment conditions.
%                   y0: dependent variable in the first time period, a N*1 vector
%                       where N is the number of individuals in the sample.
%                   y1: dependent variable in the second time period, a N*1
%                       vector where N is the number of individuals in the sample.
%                   y2: dependent variable in the third time period, a N*1 vector
%                       where N is the number of individuals in the sample.
%                   x1: exogenous independent variables in the second time period,
%                       a N*k matrix where k is the number of exogenous
%                       independent variables.
%                   x2: exogenous independent variables in the third time period,
%                       a N*k matrix where k is the number of exogenous
%                       independent variables.
%       startingvalues: starting values of parameters, a K*1 vector where K=k+1
%                       is the number of estimated parameters.
```

```
%
% Output:
%            parameter: estimated parameters, a K*1 vector.
%               stderr: standard errors of estimated parameters, a K*1 vector.
%         iterationnum: number of iterations, a scalar.
%               pvalue: p-values of Wald tests of estimated parameters, a K*1
%                       vector.
%       chisquarevalue: chisquare-value of overidentifying test, a scalar.
%            chipvalue: p-value of overidentifying test, a scalar.

N=size(x1,1);
K=size(startingvalues,1);
R=2*size(x1,2)+2;
D=NaN(R,K);

i=1;
W(:,:,i)=eye(R);
OptimizerOptions=optimset('MaxFunEvals',10000,'MaxIter',10000);
[par(:,i),objfunvalue(:,i)]=fminsearch(momentconditions,startingvalues,...
    OptimizerOptions,1,y0,y1,y2,x1,x2,W(:,:,i));

iterationnum=i;
parameter=par(:,iterationnum);
optimalweight=W(:,:,iterationnum);
optobjfunvalue=objfunvalue(iterationnum);
momentbar=feval(momentconditions,parameter,3,y0,y1,y2,x1,x2,optimalweight);
for j=1:K
    delta=zeros(K,1);
    smallvalue=max(parameter(j)*1e-5,1e-10);
    delta(j)=smallvalue;
    parnew=parameter+delta;
    D(:,j)=(feval(momentconditions,parnew,3,y0,y1,y2,x1,x2,optimalweight)-...
        momentbar)/smallvalue;
end

V=pinv(D'*optimalweight*D)/N;
stdErr=sqrt(diag(V));
tvalue=parameter./(stdErr);
pvalue=(1-normcdf(abs(tvalue),0,1))*2;
chisquarevalue=N*optobjfunvalue;
chiPvalue=1-chi2cdf(chisquarevalue,R-K);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [parameter,stdErr,iterationnum,pvalue,chisquarevalue,chiPvalue]=...
    gmmtwostep(momentconditions,y0,y1,y2,x1,x2,startingvalues)
% This function is for two-step GMM estimation for dynamic panel data model
% with three time periods.
%
% Input:
%     momentconditions: a fuction for moment conditions.
%                   y0: dependent variable in the first time period, a N*1
%                       vector where N is the number of individuals in the sample.
%                   y1: dependent variable in the second time period, a N*1
%                       vector where N is the number of individuals in the sample.
%                   y2: dependent variable in the third time period, a N*1
%                       vector where N is the number of individuals in the sample.
%                   x1: exogenous independent variables in the second time period,
%                       a N*k matrix where k is the number of exogenous
%                       independent variables.
%                   x2: exogenous independent variables in the third time period,
%                       a N*k matrix where k is the number of exogenous
%                       independent variables.
%       startingvalues: starting values of parameters, a K*1 vector where K=k+1
%                       is the number of estimated parameters.
%
% Output:
%            parameter: estimated parameters, a K*1 vector.
%               stdErr: standard errors of estimated parameters, a K*1 vector.
%         iterationnum: number of iterations, a scalar.
%               pvalue: p-values of Wald tests of estimated parameters, a K*1
%                       vector.
%       chisquarevalue: chisquare-value of overidentifying test, a scalar.
%            chipvalue: p-value of overidentifying test, a scalar.

N=size(x1,1);
K=size(startingvalues,1);
R=2*size(x1,2)+2;
D=NaN(R,K);

i=1;
W(:,:,i)=eye(R);
OptimizerOptions=optimset('MaxFunEvals',10000,'MaxIter',10000);
[par(:,i),objfunvalue(:,i)]=fminsearch(momentconditions,startingvalues,...
    OptimizerOptions,1,y0,y1,y2,x1,x2,W(:,:,i));

i=i+1;
```

```
momentilast=feval(momentconditions,par(:,i-1),2,y0,y1,y2,x1,x2,W(:,:,i-1));
W(:,:,i)=weightmatrix(momentilast);
[par(:,i),objfunvalue(:,i)]=fminsearch(momentconditions,par(:,i-1),...
    OptimizerOptions,1,y0,y1,y2,x1,x2,W(:,:,i));

iterationnum=i;
parameter=par(:,iterationnum);
optimalweight=W(:,:,iterationnum);
optobjfunvalue=objfunvalue(iterationnum);
momentbar=feval(momentconditions,parameter,3,y0,y1,y2,x1,x2,optimalweight);
for j=1:K
    delta=zeros(K,1);
    smallvalue=max(parameter(j)*1e-5,1e-10);
    delta(j)=smallvalue;
    parnew=parameter+delta;
    D(:,j)=(feval(momentconditions,parnew,3,y0,y1,y2,x1,x2,optimalweight)-...
        momentbar)/smallvalue;
end

V=pinv(D'*optimalweight*D)/N;
stdErr=sqrt(diag(V));
tvalue=parameter./(stdErr);
pvalue=(1-normcdf(abs(tvalue),0,1))*2;
chisquarevalue=N*optobjfunvalue;
chiPvalue=1-chi2cdf(chisquarevalue,R-K);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function W=weightmatrix(momentilast)
% This function computes the optimal weight matrix based on the estimated
% coefficients in last iteration.
%
% Input:
%    momentilast: a N*R moment-condition matrix where N is the number of
%                 individuals in the sample and R is the number of moment
%                 conditions for every individual.
%
% Output:
%              W: optimal weight matrix based on the estimated coefficients in
%                 last iteration, a R*R matrix.

N=size(momentilast,1);
R=size(momentilast,2);
s=zeros(R,R);
```

```
for i=1:N
    s=momentilast(i,:)'*momentilast(i,:)+s;
end

S=s/N;

W=pinv(S);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Monte Carlo Study
clear;
rng(12345);
Nindividuals=1000;
repetitions=1000;
MEstimatesOneStep=NaN(3,1,repetitions);
MstandardErrorsOneStep=NaN(3,1,repetitions);
MEstimatesTwoStep=NaN(3,1,repetitions);
MstandardErrorsTwoStep=NaN(3,1,repetitions);

for i=1:repetitions
    % true values of parameters
    par=[0.3;1;0.7];
    % individual effects
    alpha=randn(Nindividuals,1);

    % generate exogenous independent variables
    x0=[randn(Nindividuals,1)+alpha,randn(Nindividuals,1)];
    x1=[randn(Nindividuals,1)+alpha,randn(Nindividuals,1)];
    x2=[randn(Nindividuals,1)+alpha,randn(Nindividuals,1)];

    epsilon0=randn(Nindividuals,1);
    epsilon1=randn(Nindividuals,1);
    epsilon2=randn(Nindividuals,1);

    % generate the value of dependent variable in the first time period
    y0star=x0*par(2:end)+alpha+epsilon0;
    y0=max(0,y0star);

    % generate the value of dependent variable in the second time period
    y1star=par(1)*y0+x1*par(2:end)+alpha+epsilon1;
    y1=max(0,y1star);
```

```
    % generate the value of dependent variable in the third time period
    y2star=par(1)*y1+x2*par(2:end)+alpha+epsilon2;
    y2=max(0,y2star);

    startingvalues=[0;0.5;0.5];

[parameter1,stdErr1]=gmmonestep('dyFEcenmoment',y0,y1,y2,x1,x2,startingvalues);
    MEstimatesOneStep(:,:,i)=parameter1;
    MstandardErrorsOneStep(:,:,i)=stdErr1; % asymptotic standard errors

[parameter2,stdErr2]=gmmtwostep('dyFEcenmoment',y0,y1,y2,x1,x2,startingvalues);
    MEstimatesTwoStep(:,:,i)=parameter2;
    MstandardErrorsTwoStep(:,:,i)=stdErr2;

end

% means and standard deviations
aveEstimatesOneStep=mean(MEstimatesOneStep,3);
stdEstimatesOneStep=std(MEstimatesOneStep,0,3);

aveEstimatesTwoStep=mean(MEstimatesTwoStep,3);
stdEstimatesTwoStep=std(MEstimatesTwoStep,0,3);

% average asymptotic standard errors
avestandardErrorsOneStep=mean(MstandardErrorsOneStep,3);
avestandardErrorsTwoStep=mean(MstandardErrorsTwoStep,3);

disp('Summary of Results of One-step GMM')
disp('--------------------------------------------')
disp('     means     st.dev.    means of st.err.')
disp([aveEstimatesOneStep stdEstimatesOneStep avestandardErrorsOneStep])
disp('                                           ')
disp('Summary of Results of Two-step GMM')
disp('--------------------------------------------')
disp('     means     st.dev.    means of st.err.')
disp([aveEstimatesTwoStep stdEstimatesTwoStep avestandardErrorsTwoStep])
disp('                                           ')
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Estimation for the sample of Dutch natives and immigrants
% first use Stata to sort the data
% the correponding command to output the data in Stata is:
% "outsheet variables using aawholesample, comma"
```

```matlab
% input the data into Matlab
clear;
data=csv2mat_numeric('aawholesample.out');

% the number of observations
d=size(data.nomem_encr,1);

% since the data is balanced with 3 time periods, d/3 is the number of
% individuals in the sample
% denote N as the number of individuals in the sample
y0=zeros(d/3,1);
y1=zeros(d/3,1);
y2=zeros(d/3,1);

x1=zeros(d/3,3);
x2=zeros(d/3,3);

wave1=zeros(d/3,1);
wave2=zeros(d/3,1);
wave3=zeros(d/3,1);

% y0: dependent variable in the first time period, a N*1 vector
for i=1:3:(d-2)
    j=(i-1)/3+1;
    y0(j,1)=data.logfin(i,1);
    wave1(j,1)=data.wave(i,1);
end

% y1: dependent variable in the second time period, a N*1 vector
% x1: exogenous independent variables in the second time period, a N*k matrix
%     where k is the number of exogenous independent variables
for i=2:3:(d-1)
    j=(i-2)/3+1;
    y1(j,1)=data.logfin(i,1);
    x1(j,:)=[data.logincome(i,1),data.trustval(i,1),data.househead(i,1)];
    wave2(j,1)=data.wave(i,1);
end

% y2: dependent variable in the third time period, a N*1 vector
% x2: exogenous independent variables in the third time period, a N*k matrix
%     where k is the number of exogenous independent variables
for i=3:3:d
    j=(i-3)/3+1;
    y2(j,1)=data.logfin(i,1);
```

```
    x2(j,:)=[data.logincome(i,1),data.trustval(i,1),data.househead(i,1)];
    wave3(j,1)=data.wave(i,1);
end

startingvalues=[0;0;0;0];
[parameter,stdErr,iterationnum,pvalue,chisquarevalue,chiPvalue]=...
    gmmtwostep('dyFEcenmoment',y0,y1,y2,x1,x2,startingvalues);

disp('Summary of Results')
disp('--------------------------------------------')
disp('    coeff     st.err.    pvalue')
disp([parameter stdErr pvalue])
disp('                                            ')
disp('--------------------------------------------')
disp('  iteration chisquare chiPvalue')
disp([iterationnum    chisquarevalue    chiPvalue])
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Estimation for the immigrant sample
% first use Stata to sort the data
% the correponding command to output the data in Stata is:
% "outsheet variables using aaimmigrantsample, comma"
% input the data into Matlab
clear;
data=csv2mat_numeric('aaimmigrantsample.out');

% the number of observations
d=size(data.nomem_encr,1);

% since the data is balanced with 3 time periods, d/3 is the number of
% individuals in the sample
% denote N as the number of individuals in the sample
y0=zeros(d/3,1);
y1=zeros(d/3,1);
y2=zeros(d/3,1);

x1=zeros(d/3,5);
x2=zeros(d/3,5);

wave1=zeros(d/3,1);
wave2=zeros(d/3,1);
wave3=zeros(d/3,1);
```

```
% y0: dependent variable in the first time period, a N*1 vector
for i=1:3:(d-2)
    j=(i-1)/3+1;
    y0(j,1)=data.logfin(i,1);
    wave1(j,1)=data.wave(i,1);
end

% y1: dependent variable in the second time period, a N*1 vector
% x1: exogenous independent variables in the second time period, a N*k matrix
%     where k is the number of exogenous independent variables
for i=2:3:(d-1)
    j=(i-2)/3+1;
    y1(j,1)=data.logfin(i,1);
    x1(j,:)=[data.FtrDuctch(i,1),data.dutchprof(i,1),data.logincome(i,1),data.tru
    stval(i,1),data.househead(i,1)];
    wave2(j,1)=data.wave(i,1);
end

% y2: dependent variable in the third time period, a N*1 vector
% x2: exogenous independent variables in the third time period, a N*k matrix
%     where k is the number of exogenous independent variables
for i=3:3:d
    j=(i-3)/3+1;
    y2(j,1)=data.logfin(i,1);
    x2(j,:)=[data.FtrDuctch(i,1),data.dutchprof(i,1),data.logincome(i,1),data.tru
    stval(i,1),data.househead(i,1)];
    wave3(j,1)=data.wave(i,1);
end

startingvalues=[0;0;0;0;0;0];
[parameter,stdErr,iterationnum,pvalue,chisquarevalue,chiPvalue]=gmmtwostep('dyFEc
enmoment',y0,y1,y2,x1,x2,startingvalues);

disp('Summary of Results')
disp('--------------------------------------------')
disp('    coeff     st.err.   pvalue')
disp([parameter stdErr pvalue])
disp('                                            ')
disp('--------------------------------------------')
disp('  iteration chisquare chiPvalue')
disp([iterationnum    chisquarevalue    chiPvalue])
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```