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Financial Incentives, Pension Claiming, and the Value of Early Retirement Benefits

Dissertação de Mestrado

Master's dissertation presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor : Prof. Juan Rios
Co-advisor: Prof. Gustavo Gonzaga

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Abstract

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This paper studies the welfare impact of social security reforms that increase financial incentives to delay pension claiming. I leverage the 2015 Brazilian pension reform, which allowed workers past an individual-specific threshold of age and years of contribution to claim an early retirement pension with full replacement rate — a thirty percent benefit increase at the discontinuity, on average. Using novel administrative records on early retirement claims matched with labor market data, I exploit these unique and sizable incentives to estimate the substitution elasticity of pension claiming with respect to benefit size and the income elasticity of retirement. I find that claiming is not very responsive to increased financial incentives, but that labor market exit is slightly more sensitive. Next, I extend the model by Kolsrud et al. (2024) to show that these elasticities, along with the income elasticity of pension claiming, are sufficient statistics for welfare analyses whenever pension claiming and labor market exit are separate decisions. Lastly, I evaluate whether informational channels are behind the lack of responsiveness to the 2015 reform. I show that easier access to social security offices does not have a significant impact, but that local knowledge of social security rules can positively affect responsiveness to financial incentives.

Keywords

Social Security; Public Pensions; Retirement; Retirement Policies.

Resumo

Lemos, Gabriel Thomas da Justa; Rios, Juan; Gonzaga, Gustavo. **Incentivos Financeiros, Pensões Públicas e o Valor de Benefícios de Aposentadoria Antecipada**. Rio de Janeiro, 2025. 138p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Este trabalho estuda os impactos de bem-estar de reformas na previdência social que aumentam os incentivos financeiros para a postergação da aposentadoria. Eu exploro a reforma previdenciária brasileira de 2015, a qual permitiu que trabalhadores que atingissem um somatório de idade e tempo de contribuição específico solicitassem a aposentadoria com taxa de reposição integral — um aumento médio de 30% do benefício na descontinuidade. Usando novos dados administrativos sobre pedidos de aposentadoria por tempo de contribuição vinculados a dados do mercado de trabalho, eu exploro esses incentivos únicos e substanciais para estimar a elasticidade de substituição da solicitação da aposentadoria em relação ao valor do benefício e a elasticidade-renda da aposentadoria. Os resultados indicam que a solicitação da aposentadoria não é muito sensível aos incentivos financeiros, enquanto a saída da força de trabalho apresenta uma sensibilidade maior. Em seguida, eu estendo o modelo de Kolsrud et al. (2024) e mostro que essas elasticidades, juntamente com a elasticidade-renda da solicitação da aposentadoria, são estatísticas suficientes para análises de bem-estar sempre que o requerimento da aposentadoria e a saída do mercado de trabalho forem decisões separadas. Por fim, eu avalio se mecanismos informacionais ajudam a explicar a baixa sensibilidade à reforma de 2015. Eu mostro que um maior acesso a agências da previdência não tem impacto significativo, mas que o conhecimento local a respeito de regras previdenciárias pode aumentar a sensibilidade aos incentivos financeiros.

Palavras-chave

Seguridade Social; Pensões públicas; Aposentadoria; Políticas de aposentadoria.

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1
Introduction

Pension reforms have become increasingly common with an aging workforce, as social security expenditures account for 8.9% of GDP in OECD countries, and are projected to reach 10.2% by 2050 (OECD, 2023). Such policies tend to change financial incentives embedded in the pension schedule to increase fiscal sustainability of pay-as-you-go systems. However, there is strong evidence that the responsiveness to these incentives is only modest (Shoven et al., 2014; Duggan et al., 2023; Bairoliya and McKiernan, 2023; Glenzer et al., 2024; Pashchenko and Porapakkarm, 2024). In the U.S., early claiming of retirement benefits is strongly penalized but widely documented – approximately half of all Social Security beneficiaries claim before the statutory retirement age (Engelhardt et al., 2022).

A recurring feature of reforms to the pension schedule has been the introduction of more than actuarially fair adjustments for delayed claiming of benefits. For example, the Delayed Retirement Credit in the U.S. increases the pension size by 5.5-8% per year of deferred claiming past the statutory retirement age. In the framework of the social insurance literature, the introduction of such financial incentives is compelling as it combines two potentially welfare-enhancing mechanisms. First, efficiency costs could be modest as long as the claiming deferral is effective at prolonging the work life of soon-to-be retirees. Second, these reforms might provide insurance to a population particularly vulnerable to adverse shocks at old-age, such as job displacement and human capital depreciation. Nonetheless, the extent to which the lack of sensitivity to financial incentives is relevant to predict these fiscal and welfare effects is still an open question. If workers do not change claiming behavior after a pension reform that increases deferral incentives, then efficiency losses could be high[1].

Additionally, lack of knowledge about financial incentives of pension reforms might be important to explain the lack of responsiveness, with substantial implications for efficiency costs. The role of optimization frictions in reducing responsiveness to financial incentives is well established (Chetty, 2012; Kleven and Waseem, 2013), in particular for information frictions in the con-

[1]This is captured by the behavioral effect, or the change in government revenue induced by agents' re-optimizing behavior.

text of benefit schedules (Chetty et al., 2013; Gelber et al., 2020; Kostøl and Myhre, 2021). Still, whether heterogeneous impacts arise between households which are ex-ante more and less informed at the local level is yet to be explored, as well as the role of policy in reducing such disparities.

This paper evaluates the fiscal and welfare effects of pension reforms that increase financial incentives to delay early retirement claims. I exploit an unexpected 2015 Brazilian pension reform, which introduced unique and sizable incentives to delay pension claiming. As there is no earnings test to claim early retirement benefits in Brazil, I am able to separate the pension claiming and retirement decisions in a sufficient statistics approach inspired by Kolsrud et al. (2024). I leverage the exogenous variation induced by the 2015 pension reform and novel administrative records on early retirement claims, combined with the Brazilian matched employer-employee data, to estimate the relevant sufficient statistics. I then use these estimates to examine the welfare impact of the 2015 Reform. In addition, I explore possible informational mechanisms behind the responsiveness to these larger financial incentives by analyzing whether the observed responsiveness to the Brazilian pension reform was driven by ex-ante local knowledge on financial incentives and access to social security field offices.

The 2015 pension reform aimed to incentivize workers to defer early retirement claims until a new individual-specific threshold was reached[2]. Starting in June 2015, workers who achieve a sum of age and years of contribution equal to 85 for women and 95 for men became eligible to claim early retirement pensions with full replacement of their average salaries. Prior to this reform, these workers would have been eligible to receive only approximately seventy to eighty percent of their average salaries as retirement benefits. More specifically, the reform increased pension benefits by an average of thirty percent at the threshold, and this sharp discontinuity in the pension schedule generated financial incentives for workers to postpone pension claiming and to bunch at the 85/95 cutoff.

In the first part of the paper, I extend Kolsrud et al. (2024) by separating the pension claiming and labor market exit decisions. I show that the substitution and income elasticities of claiming with respect to benefit size and the income elasticity of retirement with respect to benefit size are sufficient statistics for the welfare analysis of reforms that increase pension deferral incentives. The separation of claiming and retirement behaviors is key to study the impact of a pension reform (Deshpande et al., 2024; Glenzer et al., 2024). I assume

[2]The incentives generated by this reform resemble the Delayed Retirement Credits in the U.S. (Duggan et al., 2023) and the Pensions Act of 2004 in the U.K. (Gorry et al., 2022), with the main difference arising from the fact that the Brazilian policy focuses on delaying early instead of full retirement.

that pension claiming and retirement are sequential decisions such that the substitution effect generated by a steeper pension schedule is fully absorbed by the claiming decision. Thus, a larger pension would affect labor market exit only through an income effect.

To estimate the substitution elasticity of pension claiming with respect to financial incentives, I use a difference-in-bunching design and exploit the introduction of the 85/95 cutoff to create a counterfactual for the claiming hazard had the reform not taken place. Moreover, I argue that the observed bunching is not driven by reference-points, as there are countless combinations of age and years of contribution to achieve the scores of 85/95 "points" and qualify for the pension increase after the reform. Although the observed bunching is significant, the financial incentives near the 85/95 threshold are so large that I estimate relatively small structural elasticities. I find that a 10 percent increase in benefits from further deferral reduces the probability of workers claiming their pensions one year before by 1.32 percent, on average, which is similar to previous estimates of the joint substitution elasticity of pension claiming and retirement (Manoli and Weber, 2016; Seibold, 2021).

To estimate the income elasticity of retirement with respect to benefit size, I leverage the non-anticipation of the 2015 pension reform. Discussions in Congress began in April 2015, and the reform was already implemented by June. Therefore, workers claiming their pensions in a sufficiently narrow window before this period were not able to self-select into the post-reform period in anticipation of a large pension increase. I estimate the reduced-form effect of the 2015 Reform on employment and its first-stage effect on the replacement rate by comparing workers who claimed their pensions right before with those who claimed right after the reform in an event-study design. Then, I define the income elasticity of labor supply as the reduced-form effect divided by the corresponding first-stage estimate. I find that a 10 percent increase in pension benefits raises the probability of retirement five years later by 2.7 percent. This estimate is in line with previous work focusing on the extensive margin of labor supply in the context of retirement policies (Danzer, 2013; Becker et al., 2022).

Using the estimated elasticities and the conceptual framework, I estimate the marginal value of public funds (MVPF) of the 2015 Reform. Although workers are incentivized to postpone pension claiming, which encourages later retirement, they are more likely to retire sooner once they reach the 85/95 threshold and qualify for a pension increase. As a result, the overall behavioral effect is ambiguous. I uncover the redistributive and insurance values of transferring benefits to early retirees under a consumption-based approach

(Kolsrud et al., 2024), where I leverage a survey of the Brazilian population aged 50 years or older. I estimate a fiscal externality – the ratio of behavioral to mechanical costs – equal to -0.0025, which suggests no distortionary effects. However, the willingness-to-pay for each R$1.00 of pension increase is as low as R$0.37-0.6 for a risk-aversion parameter equal to 2. Hence, the estimated MVPF ranges from 0.3 to 0.6, indicating that the 2015 Reform was probably welfare-decreasing (assuming that welfare weights are homogeneous). This finding is consistent with an already better off targeted population relative to the average Brazilian worker before the reform.

In the second part of the paper, I analyze the effect of informational mechanisms on the responsiveness to financial incentives for pension claiming, as it has been shown that providing information on social security rules may prevent workers from making suboptimal decisions (Chan and Stevens, 2008; Liebman and Luttmer, 2015; Bairolyia and McKiernan, 2024). The interaction between local knowledge about transfer schedules and reforms that change incentives is still relatively understudied although being relevant for optimal policies (Chetty et al., 2013; Kostøl and Myhre, 2021). I explore this link by combining variation in claiming incentives induced by the 2015 pension reform with variation in accessibility to social security offices and in ex-ante local knowledge about these incentives.

I use an approach inspired by Chetty et al. (2013) to identify municipalities that had greater pre-reform local knowledge about financial incentives from social security in order to evaluate the effect of such knowledge on pension claiming. Before 2015, the replacement rate of early retirement benefits depended negatively and discretely on a worker's age at the day of claiming, which created incentives for them to bunch right after their birthday in a given year. I am able to identify cities with higher and lower ex-ante knowledge of financial incentives by comparing municipalities with different degrees of bunching. I then employ a dynamic difference-in-differences specification to compare individuals from municipalities with more versus less ex-ante local knowledge. Existing evidence points to the importance of social networks in transmitting knowledge about claiming deferral incentives (Oral et al., 2024). Thus, heterogeneous responses to the 2015 reform could arise due to differences in local knowledge. I find that workers from more informed municipalities are 39.2% more likely to bunch at the 85/95 cutoff two years later, relative to the baseline. I also estimate a positive and significant effect on benefit size equal to 6.6% of the control baseline.

Finally, I employ a fuzzy RD design to study the impact of more access to social security on pension claiming behavior by exploiting a population-size discontinuity for the location of field offices. In 2009, the Brazilian Social Security Agency decided to expand its network of field offices to all municipalities with at least 20 thousand residents in 2007. Higher accessibility to an office should boost responsiveness to financial incentives by increasing local salience of social security rules and reducing application costs (Deshpande and Li, 2019). I find that greater accessibility leads people to claim pensions 48.6% more at their municipality of residence but, unexpectedly, does not increase their responsiveness to the reform-driven incentives. In fact, all pension-related outcomes are statistically insignificant at the discontinuity. These results suggest that either social security workers were not effectively delivering information on pension deferral incentives, or that individuals were informed at the offices but were too impatient to return later when they became eligible to the higher pension.

Overall, these results have several policy implications. I find that social security reforms which increase financial incentives of pension deferral can be efficient, as the estimated ratio of behavioral to mechanical costs of the 2015 Reform is approximately zero. However, welfare effects also depend on the relative need for insurance of the targeted population, which I estimate to be low in my context. Whether a similar reform could have been welfare-increasing if the targeted group were relatively worse off is uncertain, as the efficiency cost would likely be higher if their responsiveness to financial incentives were even lower – which I show to be true for low earnings individuals. Moreover, I provide evidence that local information can be key to generate responsiveness to pension reforms. While greater access to social security field offices did not impact the responsiveness to the 2015 pension reform, I estimate that more ex-ante local knowledge about incentives from social security generated a larger response to the newly-introduced deferral incentives. If new incentives are not well-informed by policymakers, then pension reforms might enhance preexisting inequalities.

This paper contributes to three strands of the literature. First, I contribute to the large empirical literature that identifies the impacts of social security reforms on pension claiming and labor market exit (Mastrobuoni, 2009; Behagel and Blau, 2012; Staubli and Zweimüller, 2013; Brown, 2013; Manoli and Weber, 2016; Seibold, 2021; Dolls and Krolage, 2023; Rabaté et al., 2024), especially of pension reforms that explicitly incentivize claiming deferral (Gorry et al., 2022; Duggan et al., 2023). The existing evidence has found that retirees are not very responsive to financial incentives from the pension schedule, but most papers focus on contexts where these incentives are not very large, which could dampen responsiveness if information acquisition is costly. I contribute to this literature by exploring a pension reform with unusually large deferral incentives, in a context where pension claiming and labor market exit are separate decisions as there is no retirement earnings test in Brazil. Lalive et al. (2023) also explores both of these response margins separately, but I combine reform-based variation with a bunching approach to uncover the impact on claiming. I find that the responsiveness to the 2015 Reform is limited even though financial incentives are large, with an average structural elasticity of pension claiming of -0.132. I also contribute to the existing literature by providing evidence from a developing country, while previous work has mostly focused on developed economies. To the best of my knowledge, de Carvalho Filho (2008) and McKiernan (2022) are the only other papers that explore pension reforms in Brazil, but the first focuses on the labor supply responses from rural workers and the second sets up a structural model to study an increase to the statutory retirement age in 2019.

Second, I contribute to the growing literature on the welfare effects of social security reforms using sufficient statistics. Haller (2022) and Kolsrud et al. (2024) have recently shown that insights from the sufficient statistics literature can be extended to analyze pension policies. I improve upon earlier work by separating pension claiming from labor market exit in the derivation of novel sufficient statistics for welfare analyses. These decisions can be tied through earnings tests, whereby workers cannot receive retirement benefits if they are still active in the labor force. Nonetheless, many developed and developing countries do not present this instrument or are discussing its extinction (Börsch-Supan et al., 2018). In addition, pension claiming and retirement behaviors may react differently to pension reforms (Deshpande et al., 2024; Glenzer et al., 2024), such that a separate analysis is essential even when earnings tests are present. I find that the pension claiming responsiveness to financial incentives is instrumental to correctly predict the fiscal externality of reforms to the pension schedule.

At last, I contribute to the literature that explores the effect of information on the responsiveness towards transfer policies, including pension claiming (Mastrobuoni, 2011; Chetty et al., 2013; Liebman and Luttmer, 2015; Brinch et al., 2017; Kostøl and Myhre, 2021; Caplin et al., 2022; Glenzer et al., 2024). Previous work indicates that the small responsiveness to financial incentives from social security are partially caused by frictions in pension claiming decisions (Gelber et al., 2020; Bairoliya and McKiernan, 2023). However, the relationship between information about social security and new reform-based incentives is still underexplored due to the difficulty in simultaneously assessing a reform with sharp financial incentives and identifying individuals with varying degrees of ex-ante knowledge. I extend this literature by estimating the impact of accessibility to field offices and of ex-ante local knowledge about social security rules on the responsiveness to reform-driven financial incentives.

The remainder of the paper proceeds as follows. Section 2 presents the conceptual framework for examining how benefit size impacts pension claiming and retirement decisions. Section 3 discusses the institutional context of Brazilian retirement pensions and the data. Sections 4 and 5 present the effects of the reform on pension claiming and labor market exit, respectively. Section 6 implements the welfare analysis. Section 7 presents the mechanisms of knowledge and responsiveness to financial incentives. Section 8 discusses the policy implications and concludes.

2
Conceptual Framework

In this section, I present the conceptual framework that separates the pension claiming and labor market decisions in the individual problem, and derives the relevant sufficient statistics formula for the welfare analysis. This framework is an extension of the individual problem from Manoli and Weber (2016) and of the welfare analysis from Kolsrud et al. (2024), where I incorporate the pension claiming decision into the government's budget constraint. Appendix B presents additional details.

2.1
Model of Individual Behavior

2.1.1
Setup

I consider a forward-looking worker deciding sequentially when to claim an early retirement pension and when to exit the labor force. There are three states: working and deferring the pension (W), working while collecting the pension (K) and retirement (R). In each month t relative to the eligibility period, agent i decides her consumption level and whether to transition or not to the next stage, given her expectation of the following period's state-contingent utilities. Financial incentives to postpone pension claiming are depicted by the pension schedule $B = \{b_j\}_{j=0}^{T}$ (Figure 2.1). For each additional period of claiming deferral, retirement benefits are permanently increased due to a higher replacement rate. The permanent reduction in retirement benefits due to early claiming is present in most countries, and actuarial fairness is rarely perfect (Shoven et al., 2014).

The uncertainty in decision-making arises from disutilies of claiming deferral $\phi_t^i = \rho\phi_{t-1}^i + \nu_t^i$ and of working $\alpha_t^i = \rho\alpha_{t-1}^i + \psi_t^i$, which are stochastic processes. Heterogeneity is present in the model due to the inclusion of disutility shocks $\psi_t^i \sim L(\theta^i)$ and $\nu_t^i \sim Q(\zeta^i)$, with individual parameters $\theta^i \in \Theta$ and $\zeta^i \in Z$. The intuition behind the disutility of deferral ϕ_t^i is that the postponement of pension claiming entails an opportunity cost from not receiving a steady source of income today, magnified by impatience. At each period t, worker i chooses the assets and the transition between states for the next period, $k_t^i = \mathbb{1}(i \text{ claims at } t+1)$ and $r_t^i = \mathbb{1}(i \text{ retires at } t+1)$.

2.1.2 Individual Problem and Behavior

The individual budget set in each state is given by:

$$\begin{cases} c_t^{i,W} + R_{t+1}a_{t+1}^i \leq R_t a_t^i + w^i(1-\tau) \\ c_t^{i,K} + R_{t+1}a_{t+1}^i \leq R_t a_t^i + w^i(1-\tau) + b(\kappa^i) \\ c_t^{i,R} + R_{t+1}a_{t+1}^i \leq R_t a_t^i + b(\kappa^i) \end{cases}$$

where $c_t^{i,j}$ is consumption in state $j \in \{W, K, R\}$, w^i is labor income, τ is income tax, a_t^i are assets, R_t is the gross real interest rate, and $\kappa^i = min_j(\{j \geq 0 : k_j^i = 1\})$ is the period in which individual i claims the pension. The state variables in period t are summarized by $\Omega_t^i = (\{a_j^i\}_{j=0}^t, \{\nu_j^i\}_{j=0}^t, \{\psi_j^i\}_{j=0}^t)$. For a given Ω_t^i, worker i chooses (a_{t+1}, k_t^i, r_t^i) that maximize the expected present value of her flow utilities discounted by the disutility shocks[1]. Therefore, individual behavior is characterized by the following value functions[2]. Appendix Figure B1 depicts the decision tree of the worker.

$$\begin{aligned} V_t^W(\Omega_t) = \max_{a_{t+1}} u(R_t a_t - R_{t+1}a_{t+1} + w(1-\tau)) - \phi_t - \alpha_t + \\ \beta \mathbb{E}_t \Big[\max_{k_t \in \{0,1\}} k_t V_{t+1}^K(\Omega_{t+1}) + (1-k_t) V_{t+1}^W(\Omega_{t+1}) \Big] \end{aligned} \tag{2-1}$$

$$\begin{aligned} V_t^K(\Omega_t) = \max_{a_{t+1}} u(R_t a_t - R_{t+1}a_{t+1} + w(1-\tau) + b(\kappa)) - \alpha_t + \\ \beta \mathbb{E}_t \Big[\max_{r_t \in \{0,1\}} r_t V_{t+1}^R + (1-r_t) V_{t+1}^K(\Omega_{t+1}) \Big] \end{aligned} \tag{2-2}$$

$$V_t^R = \max_{a_{t+1}} u(R_t a_t - R_{t+1}a_{t+1} + b(\kappa)) + \beta V_{t+1}^R \tag{2-3}$$

The optimal strategies of claiming and labor market exit are described by reservation disutilities, where worker i claims the pension if $\phi_t^i \geq \bar{\phi}_t^i$ and retires if $\alpha_t^i \geq \bar{\alpha}_t^i$. The underlying assumption is that claiming and retirement are sequential decisions. Agent i compares her value of deferring the pension with the value of claiming and staying in the labor force, disregarding the value of retiring. Hence, $\bar{\phi}_t^i$ is determined by $V_t^W(\Omega_t(\bar{\phi}_t^i)) = V_t^K(\Omega_t^i)$, and $\bar{\alpha}_t^i$ by $V_t^K(\Omega_t(\bar{\alpha}_t^i)) = V_t^R(\Omega_t^i)$. The reservation disutilities can then be written using Taylor approximations as $\bar{\phi}_t \approx -u'(R_t a_t - R_{t+1}a_{t+1} + w(1-\tau))b(t) + \beta OV_t^K$

[1] I assume that flow utilities $u^i(\cdot)$ are increasing, concave, and depend only on consumption.

[2] For clarity, I omit the i superscript.

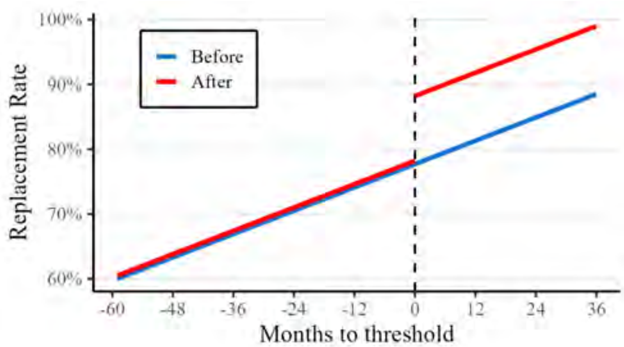
and $\bar{\alpha}_t \approx u'(R_t a_t - R_{t+1}a_{t+1} + b(t))w(1-\tau) + \beta OV_t^R$. Note that $OV_t^K \equiv \mathbb{E}_t\{\max(V_{t+1}^W, V_{t+1}^K) - \max(V_{t+1}^R, V_{t+1}^K)\}$ is the option value of delaying the claim of early retirement benefits. If she delays her claim, then the worker preserves the option of claiming a higher pension in future periods (Stock and Wise, 1990), at the cost of higher work and deferral disutilities and fewer accrual periods. Similarly, $OV_t^R \equiv \mathbb{E}_t\{\max(V_{t+1}^K, V_{t+1}^R) - V_{t+1}^R\}$ is the option value of not retiring at time t. This value captures the opportunity cost of retiring earlier, given by the foregone labor income.

Given the derived reservation disutilities, I characterize the claiming hazard and the labor market exit distributions for each month since eligibility. The claiming hazard is the probability that worker i claims her pension at period t conditional on not having claimed yet, and is given by $CH(t;B) = \Pr(\phi_t \geq \bar{\phi}_t \mid \phi_{t-1} < \bar{\phi}_{t-1})$. The labor market exit distribution is the cumulative probability that agent i has retired by time t, conditional on having claimed the pension, and is given by $S(t;B) = \Pr(\alpha_t \geq \bar{\alpha}_t \mid \phi_{t-1} \geq \bar{\phi}_{t-1})$. Additionally, I describe the claiming distribution as the cumulative probability that the worker has claimed the pension by period t, which is given by $D(t;B) = \Pr(\phi_t \geq \bar{\phi}_t)$.

2.1.3 Predictions for Pension Reforms

I use the model of individual behavior to interpret the effect of policy changes dB to the pension schedule on the claiming and retirement decisions (see Appendix B for more details). Consider the pension reform depicted in Figure 2.1 that increases benefits for those deferring the claim at least until $\bar{t}$ months since eligibility, such that $\Delta b_t > 0$ for $t \geq \bar{t}$. This reform negatively impacts the claiming behavior for those who would have claimed prior to $\bar{t}$ via a substitution effect. Note that $b(t)$ is unchanged and that OV_t^K increases

Figure 2.1: Stylized pension reform to retirement benefits



Note: This figure plots the replacement rate of early retirement benefits for each distance in months to the threshold $\bar{t}$, both before and after a pension reform which increases financial incentives of deferral.

for $t < \bar{t}$. Thus, $\bar{\phi}_t$ also increases due to the steeper pension schedule. The decrease in $CH(t;B)$ captures only a substitution effect as the relative price of claiming at period t, with respect to deferring until $\bar{t}$, has changed, while the marginal utility of the individual is unchanged. In contrast, this reform positively affects the claiming hazard for those who had already postponed claiming past $\bar{t}$ through an income effect[3]. The worker experiences an increase in the social security benefits that she is eligible to claim at $t \geq \bar{t}$, without any price distortion in the decision to defer claiming for additional periods. Hence, $\bar{\phi}_t$ decreases only due to the marginal utility of consumption, which implies that $D(t;B)$ increases via an income effect.

The labor market exit decision changes for those who claim after $\bar{t}$ due to an income effect. Conditional on claiming the pension after time $\bar{t}$, social security benefits should be larger. This implies that the values of states K and R both increase due to the marginal utility of consumption, which leads to a change in OV_t^K via an income effect. Also, marginal utilities are directly affected thanks to the larger pension such that $\bar{\alpha}_t$ decreases and $S(t;B)$ increases through an income effect. Meanwhile, the retirement decision of agents who claim their pension before the cutoff $\bar{t}$ is unchanged in spite of the reform, given that the benefit size is constant.

In summary, changes in $CH(t;B)$ and $S(t;B)$ that result from the change in the pension schedule are characterized by the substitution elasticity of claiming with respect to financial incentives $\varepsilon_{CH}^{t-\bar{t}} \equiv \frac{\partial CH(t)}{\partial(b_{\bar{t}}/b_t)} \frac{b_{\bar{t}}/b_t}{CH(t)} < 0$, which I allow to differ based on the distance to the cutoff, the income elasticity of claiming with respect to benefits $\eta_D \equiv \frac{\partial D(t)}{\partial a_t} \frac{a_t}{D(t)} > 0$, and the income elasticity of retirement with respect to benefits $\eta_S^{t-\kappa} \equiv \frac{\partial S(t)}{\partial a_t} \frac{a_t}{S(t)} > 0$ (or the negative of the elasticity of labor supply, analogously), which can also differ each period since claiming. I estimate $\{\varepsilon_{CH}^{t-\bar{t}}\}_t$ and $\{\eta_S^{t-\kappa}\}_t$ in Sections 4 and 5, where I use reduced-form methods and leverage variation induced by a Brazilian pension reform.

2.2 Welfare Analysis

I describe the way in which the pension reform dB that increases financial incentives to delay claiming affects government revenue and welfare. Consider that benefits are increased by $\delta\%$ for workers who defer claiming until $\bar{t}$ periods since eligibility, such that $\Delta b(t) = \delta b(t)$ if $t \geq \bar{t}$ (Figure 2.1). This reform is similar to other pension policies that increase the steepness of the pension schedule to incentivize later claiming by rewarding delayed retirement, such

[3]Assuming that consumption is a normal good.

as the Delayed Retirement Credit (Duggan et al., 2023). Next, I show that the elasticities highlighted in the model predictions are informative about the marginal value of public funds from this pension policy (Hendren and Sprung-Keyser, 2020).

2.2.1 Mechanical and Behavioral Effects

To analyze the welfare effect of the pension reform in a simple economy, I consider a government budget constraint equal to $GBC(B) \equiv N\sum_{t=0}^{T} R^{-t}\{\bar{\tau}[1 - S(t)D(t)] - \bar{b}_t D(t)\}$, where the first term represents income tax collection, the second term represents social security expenditures[4] and N is the number of retirees. The government budget constraint depends on the cumulative probability function of retirement $S(t; B)$, the real average tax paid by workers after eligibility $\bar{\tau}$, and the real average social security benefit $\bar{b}_t$ for workers claiming at t. This analysis extends the government budget constraint from Kolsrud et al. (2024), as their model couples pension claiming and retirement into a single decision. While I derive the welfare effect based on this specific formula for revenue below, the implementation in Section 6 is more general.

The net cost TC of this pension reform consists of a mechanical cost MC and a behavioral cost BC such that $TC = MC + BC$. The mechanical effect is the hypothetical change in revenue holding agents' behavior constant but changing the pension schedule. Given the government budget constraint above, I define the mechanical cost as $MC = N\sum_{t=0}^{T} R^{-t}\Delta\bar{b}_t D(t)$, where $\Delta\bar{b}_t = \mathbb{1}(t \geq \bar{t}) \cdot \bar{b}_t \cdot \delta$. Therefore, assuming $R = 1$, I find that the mechanical cost is:

$$MC = \delta N \sum_{t=\bar{t}}^{T} \bar{b}_t D(t) \tag{2-4}$$

The behavioral effect is the hypothetical change in revenue holding the pension schedule fixed but letting workers adjust their behavior after the reform. The change in behavior due to the pension reform depends on both the change in pension claiming for each period t relative to $\bar{t}$, $\Delta D(t)$, as well as the change in the labor supply, $\Delta S(t)$. The behavioral cost is given by $BC = N\sum_{t=0}^{T} R^{-t}\Big\{\bar{\tau}_t\Big[\Delta S(t)D(t) + S(t)\Delta D(t)\Big] + \bar{b}_t\Delta D(t)\Big\}$, and its evaluation relies in the estimation of $\Delta D(t)$ and $\Delta S(t)$. I derive the change in behavior as a function of the relevant elasticities, based on the predictions from the model of individual optimization. The variation $\Delta D(t)$ depends on

[4] Note that the first term multiplies the cumulative probabilities of claiming and retirement given the assumption that these decisions are sequential. If workers claim their pensions sooner, this will have a direct effect on income tax collection even if the probability of labor market exit for each period relative to claiming remains constant.

the timing since eligibility. For workers who would have claimed at $t < \bar{t}$, pension claiming is affected by the increase in financial incentives of deferral at $\bar{t}$ such that $\Delta D(t) = \frac{\partial D(t)}{\partial(b_{\bar{t}}/b_t)}\Delta(b_{\bar{t}}/b_t) = \delta\varepsilon_D^{t-\bar{t}}D(t)$. For workers that would have claimed past the threshold $t \geq \bar{t}$, pension claiming is impacted only via the income effect of benefit size at t which implies $\Delta D(t) = \frac{\partial D(t)}{\partial b_t}\Delta b_t = \delta\eta_D D(t)$. Meanwhile, $\Delta S(t)$ is described as follows. Labor market exit will be impacted only through the income effect of pension benefits on labor supply. Thus, $\Delta S(t) = \frac{\partial S(t)}{\partial b_t}\Delta b_t = \delta\eta_S^{t-\bar{\kappa}}S(t)$ for $t \geq \bar{t}$. At last, I substitute the behavioral changes in pension claiming and labor supply into the behavioral cost:

$$BC = \delta N\left\{\underbrace{\sum_{t=0}^{\bar{t}-1}\left[\bar{\tau}S(t) + \bar{b}_t\right]\varepsilon_D^{t-\bar{t}}D(t)}_{\substack{\text{Revenue increase}\\ \text{due to claim deferral}}} + \underbrace{\sum_{t=\bar{t}}^{T}\left[\bar{\tau}(\eta_S^{t-\bar{\kappa}} + \eta_D)S(t) + \bar{b}_t\eta_D\right]D(t)}_{\substack{\text{Revenue decrease due to earlier}\\ \text{retirement and claiming after } \bar{t}}}\right\} \tag{2-5}$$

The expression above highlights the way that responsiveness to financial incentives affects the fiscal impact from a pension reform due to behavioral changes. On the one hand, increasing deferral incentives has a positive effect on revenue as workers delay their claiming period to receive a higher pension. Once workers claim later, their labor market exit is also postponed, which further increases revenue through increased tax collection. This behavior is governed by the substitution elasticity of claiming ($\varepsilon_D^{t-\bar{t}} < 0$). On the other hand, the surge in financial incentives comes at the cost of higher pension payouts when these workers effectively claim social security. Government revenue is negatively impacted since an income effect drives workers to exit the labor force sooner, decreasing income tax collection. Also, the eligibility to a higher pension creates another income effect which incentivizes workers to claim their pensions earlier once the threshold $\bar{t}$ is achieved. These behaviors are governed by the income elasticities of labor market exit and claiming ($\eta_S^{t-\bar{\kappa}}$, $\eta_D > 0$).

2.2.2 Welfare Effect

I define the welfare effect from the pension reform in terms of the MVPF (Hendren and Sprung-Keyser, 2020), which measures the impact on welfare from a wide range of policies. The MVPF is defined as the aggregate willingness-to-pay for the policy divided by the net cost to the government, $MVPF \equiv WTP/(MC + BC)$. A policy is welfare-increasing when the MVPF is greater than one, assuming that welfare weights are homogeneous. Note that the aggregate willingness-to-pay for the pension reform can be decomposed as the willingness-to-pay for each dollar transferred to the targeted group g, $WTP_g^{\$1}$, multiplied by the total pension increase, which is equal to the mechanical cost of the reform: $WTP \equiv WTP_g^{\$1} \times MC$. I follow Kolsrud et al. (2024) and write the willingness-to-pay for each dollar as the social marginal utility of the targeted group $SMU_g \equiv \mathbb{E}[\omega_i \partial_c u^i(c) \mid i \in g]$, where ω_i stands for i's welfare weight, divided by the marginal cost of public funds λ, such that $WTP \equiv SMU_g/\lambda \times MC$. Therefore, the pension reform is welfare-increasing if $MVPF = \frac{SMU_g/\lambda}{1+BC/MC} \geq 1$, where the denominator captures the fiscal externality or the ratio of behavioral to mechanical costs.

Kolsrud et al. (2024) define the consumption smoothing effect from stylized pension reforms by linking differences in marginal utilities to differences in consumption. I follow their consumption-level implementation and describe the willingness-to-pay for each dollar of pension increase as:

$$WTP_g^{\$1} \equiv \frac{SMU_g}{\lambda} \approx \frac{SMU_g}{SMU_{pop}} \approx 1 + \gamma \underbrace{\frac{\mathbb{E}[C_i \mid i \in pop] - \mathbb{E}[C_i \mid i \in g]}{\mathbb{E}[C_i \mid i \in pop]}}_{\equiv \Delta C} \tag{2-6}$$

where $\gamma \equiv -\frac{\partial_{cc} u^i(C_i)}{\partial_c u^i(C_i)} C_i$ is the risk-aversion parameter and C_i is the consumption-level of individual i. There are two assumptions for this consumption-based approach to hold. First, I assume that the marginal cost of public funds is approximately equal to the average social marginal utility from the whole population, $\lambda \approx SMU_{pop}$, such that the cost of having a dollar in public funds is equal to the value from transferring this dollar to the population in a lump-sum fashion. Second, the marginal utility of consumption *conditional on consumption* should be homogeneous across these groups. Kolsrud et al. (2024) leverage the richness of their data to show that this assumption seems reasonable in the Swedish context by comparing the composition of consumption from different groups of retirees.

Finally, using Equations (2-4), (2-5) and (2-6), the MVPF of the pension reform dB can be expressed as:

$$MVPF = \frac{1 + \gamma \Delta C}{1 + \frac{\sum_{t=0}^{\bar{t}-1} \left[\bar{\tau} S(t) + \bar{b}_t\right] \varepsilon_D^{t-\bar{t}} D(t) + \sum_{t=\bar{t}}^{T} \left[\bar{\tau}(\eta_S^{t-\bar{\kappa}} + \eta_D) S(t) + \bar{b}_t \eta_D\right] D(t)}{\sum_{t=\bar{t}}^{T} \bar{b}_t D(t)}} \tag{2-7}$$

The expression above indicates that the substitution elasticity of pension claiming and the income elasticities of labor market exit and claiming are sufficient statistics for the welfare effect of this policy. A greater sensitivity to deferral incentives (i.e., a highly negative $\varepsilon_D^{t-\bar{t}}$), leads to a larger increase in government revenue, making the reform more efficient. Conversely, if labor market exit is highly responsive to increased benefits (i.e., a highly positive $\eta_S^{t-\bar{\kappa}}$), the reform becomes less efficient, as workers exit the labor force earlier. Lastly, if pension claiming is highly sensitive to already-eligible social security benefits (i.e., a highly positive η_D), more bunching at $\bar{t}$ will be observed, reducing the policy's efficiency. Thus, the efficiency of a pension reform that strengthens financial incentives for deferral ultimately depends on the relative magnitudes of $\varepsilon_D^{t-\bar{t}}$, $\eta_S^{t-\bar{\kappa}}$ and η_D, which is an empirical question.

3
Institutional Background and Data

In this section, I present some institutional details about public pensions in Brazil and discuss the 2015 pension reform. I also introduce the sample of interest derived from novel administrative records of early retirement claims matched with the Brazilian employer-employee data.

3.1
Institutional Background

Public pensions are the main source of income for retired Brazilian workers[1]. According to the Brazilian National Health Survey (IBGE, 2019), the share of total income relative to public pensions is equal to 15.54% and 81.46%, on average, for workers who are 55 and 75 years old. These shares are even higher once I restrict the analysis to those who receive any public pensions, reaching 82.55% and 92.24%, respectively. Social security expenditures in Brazil are in par with more developed economies and were equal to 9.16% of the 2023 GDP, while contributions were only 5.76% of GDP in the same year.

Formal workers contribute mandatorily to social security by paying a tax of 8-11% of their monthly salary[2], while firms contribute via a 20% payroll tax. The public pension system follows a defined-benefit scheme, and there are two main regimes: the *Regime Geral de Previdência Social* (RGPS), intended for private-sector workers, and the *Regime Próprio de Previdência Social* (RPPS), for public-sector workers. The former concentrates the bulk of public pension payments, and accounts for 90.51% of total expenditures (TCU, 2023). Although the RGPS distinguishes between urban and rural workers, 69.19% of the 32 million private-sector retirees in 2023 were urban (MPS, 2023). Therefore, I focus on private-sector urban retirees, who not only account for the main share of expenditures but are also the predominant recipients of early retirement pensions, as 99.62% of all early-retirees are urban.

[1]Occupational and private pensions are rare and restricted to the upper tail of the income distribution. Only 4.9% of Brazilians above 50 years old receive private pensions (FIOCRUZ, 2022).

[2]Until 2019, tax brackets and the corresponding tax rates were 8% until R$1751.81, 9% from R$1751.82 to R$2919.72 and 11% from R$2919.73 to R$5839.45. Earnings above this threshold are exempt.

Urban workers are eligible for a full retirement pension (*Aposentadoria por Idade*) upon reaching the statutory retirement ages of 60 for women and 65 for men with 15 years of contribution. Alternatively, they may claim an early retirement pension (*Aposentadoria por Tempo de Contribuição*) provided they have completed a minimum of 30 years of contribution for women and 35 for men[3]. Notably, there was no minimum age to claim an early retirement pension in Brazil before 2019, when these rules were overhauled in a major pension reform (McKiernan, 2022). In 2023, early retirement pensions represented 35.35% of all old-age retirement pensions in Brazil, a share that increases to 55.18% once I restrict to urban workers (MPS, 2023). The full retirement pension pays a benefit equivalent to the average of the 80% highest monthly wages received by an individual between July 1994 and the claiming month, adjusted by inflation[4], while early retirement pensions pay this average discounted by a factor known as the *fator previdenciário*. All benefits are capped on the lower end by the minimum wage and at the upper end by the *teto previdenciário*, equivalent to R$5.839.45 (5.6 minimum wages) in 2019[5]. However, this upper cap is not binding for the majority of the population, since it is located at approximately the 90th individual income percentile in Brazil.

The *fator previdenciário* determines the replacement rate of the benefit as a function of age, years of contribution, and survival expectancy of an individual with a given age at a given year[6]. It essentially creates a steepness in the pension schedule: the older an individual is at the time of claiming, and the more years she has contributed, the higher the early retirement pension she is eligible to claim. This discount factor was not designed to be actuarially-fair, but rather to directly incentivize claiming deferral[7]. Figure 3.1 Panel A depicts the average benefit schedule for a Brazilian worker considering early

[3]There are also disability pensions, which I do not take into account in the analysis since they are closer in nature to disability insurance than to old-age retirement pensions.

[4]This is equivalent to the Primary Insurance Amount (PIA) from the US. Wages prior to July 1994 are not considered in the calculation due to hyperinflation pre-monetary stabilization program (*Plano Real*).

[5]For clarity, I define the Actuarial Replacement Rate as the ratio of the benefit amount to the worker's average salary, considering caps at the minimum wage and the *teto previdenciário*. In contrast, the Actual Replacement Rate is the ratio of the benefit amount to the worker's average salary without any caps. See Appendix Figure C3 for more details.

[6]More specifically, this factor is given by $f(y) = \frac{0.31 \cdot C(y)}{SE(y)}\left[1 + \frac{A(y) + 0.31 \cdot C(y)}{100}\right]$, where A is age at year y, C is years of contribution at year y, and SE is the survival expectancy of an individual with age A, calculated yearly by the Brazilian Institute of Geography and Statistics (IBGE). Note that A and C are continuous variables, such that months and days are taken into account in the calculation, while SE is a discrete function of age. For women, 5 years are added to the years of contribution considered in the calculation of the discount factor.

[7]Note that the *fator previdenciário* can also be greater than one, such that it increases benefit replacement after several deferral years, up to the *teto previdenciário* cap.

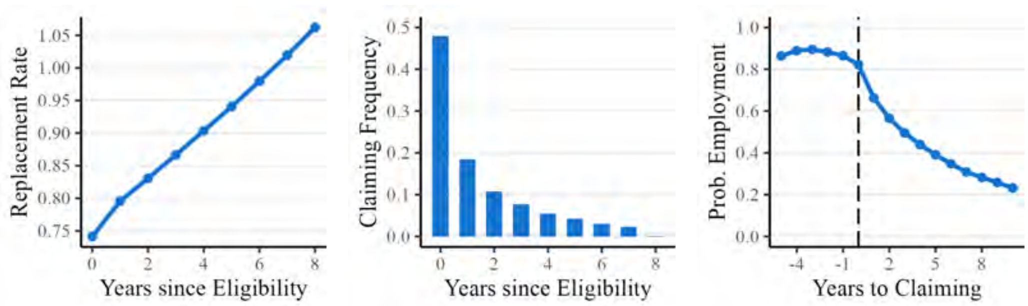
retirement, as a function of deferral years since eligibility. The timing of pension claiming is an irreversible and life-defining decision, as individuals are unable to claim an early retirement pension and recalculate their benefit size in the future after additional years of contribution and older age.

Much like in the U.S. and other developed economies, Brazilian workers are not very responsive to deferral incentives from the pension schedule. Figure 3.1 Panel B plots the histogram of pension claiming for each year since eligibility. In spite of a high discount factor and large deferral incentives, almost 50% of workers claim as soon as they are eligible, and no more than 25% choose to postpone claiming for more than 2 years. Combined with the fact that public pensions are the primary source of income for Brazilian retirees, this lack of responsiveness to financial incentives suggests that workers might not be optimizing their claiming decisions. In fact, only 20.4% of Brazilians nearing retirement or already retired have planned their financial health for the future (FIOCRUZ, 2022).

Unlike the U.S. and most OECD countries, Brazil does not have an earnings test for early retirement benefits. Hence, workers can claim their pensions and continue working without having their benefits withdrawn. Figure 3.1 Panel C depicts the probability of having a formal job for each year relative to early retirement claiming. As laid out in the conceptual framework, pension claiming and retirement can be viewed as sequential decisions, since workers gradually leave the labor force after claiming their pensions. This seems to be true especially for claimants with higher income. Appendix Figure C1 Panel B highlights that the average salary conditional on formal employment is increasing with age. Also, those who claim their pension at a younger age are

Figure 3.1: Despite large financial incentives, few workers choose to defer claiming in Brazil

A. Pension schedule **B.** Frequency of claims **C.** Prob. employment



Note: The figure shows descriptive statistics for the Brazilian context using the SUIBE-RAIS full sample. Panel A depicts a stylized pension schedule, as the average benefit replacement rate for each year of pension claiming deferral since eligibility. Panel B shows the histogram of claims for each year since eligibility. Panel C depicts the probability of working in a formal job for each year relative to the pension claiming period.

more likely to persist in formal employment after claiming. Appendix Figure C2 decomposes this trend by age and suggests a higher probability of retirement for those who were at least 55 years old when they claimed their pension.

Until recently, Brazilian workers were required to claim their pensions in-person at social security field offices run by the Brazilian Social Security Agency (INSS). These field offices also acted as places where the worker could inform herself about eligibility to claim a pension. However, only about one-fifth of Brazilian municipalities had a social security office up to 2009, such that hassles and travel costs were common issues. In 2009, the INSS decided to expand its physical presence by opening offices at every Brazilian municipality with more than 20 thousand residents. The plan was to create 720 additional offices, almost doubling the network of approximately one thousand offices.

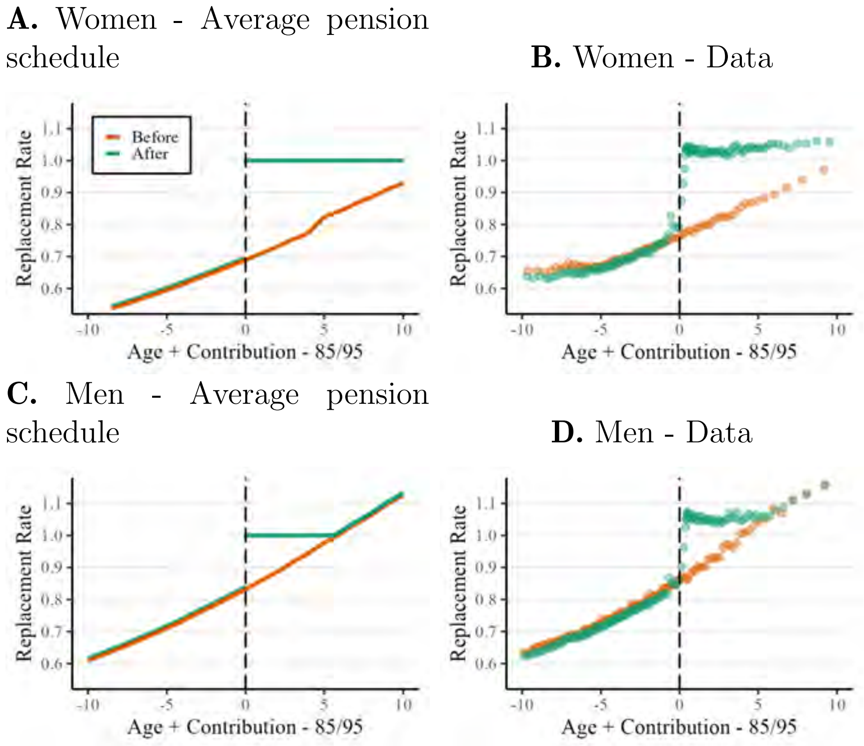
3.1.1 The 2015 Reform

Social security rules for private-sector workers were unchanged since 1999, the year in which the *fator previdenciário* was introduced to incentivize claiming deferral. Since then, worker unions regularly petitioned for its end due to benefits being heavily discounted, but these requests were mostly ignored as a result of fiscal concerns. However, the Brazilian Congress unexpectedly changed how early retirement benefits were calculated in June 2015. In particular, 2015 was a pivotal year because it marked the beginning of an economic and political crisis that would culminate with the impeachment of the president in 2016, after losing political support in the Brazilian Congress.

The 2015 pension reform created an alternative rule to calculate the replacement rate that increased early retirement benefits. In the case of workers who achieved a sum of age and years of contribution (continuous variables) of 85 "points", for women, and 95, for men, the discount factor would no longer apply to the calculation of the benefit. At the 85/95 threshold, the replacement rate would automatically be 100% of the average individual salary – an average pension increase of 20% and 35% for men and women, respectively. Figure 3.2 illustrates how the pension schedule changed, creating large incentives to bunch at the 85/95 discontinuity. The amount of deferral years DY_i necessary for a woman with eligibility age EA_i (a continuous variable) to bunch exactly at the discontinuity is given by $DY_i = (85 - EA_i - 30)/2$[8]. Therefore, as workers achieve the minimum years of contribution of 30 and 35 at different eligibility ages, this reform essentially created an individual-specific discontinuity to be eligible to the pension increase. Furthermore, this new rule was not retroactive,

[8]Assuming she does not leave the workforce prior to claiming her pension.

Figure 3.2: The 2015 Reform introduced sizable claiming deferral incentives until the 85/95 threshold



Note: The figure plots the pension schedules for women and men, both before and after the 2015 Reform. The x-axis represents the Age + Years of contribution - 85/95 the worker had at claiming, and the y-axis the corresponding benefit replacement rate. Panels A and C plot stylized pension schedules using the official parameters, while Panels B and D plot the pension schedules observed directly in the SUIBE-RAIS full sample using a binscatter plot (Cattaneo et al., 2024).

such that workers who claimed their pensions prior to June 2015 could not recalculate their benefit size.

The political landscape from 2015 was largely responsible for the unexpected introduction of this alternative rule for calculating early retirement benefits. After the historically close 2014 presidential reelection, the government put forth an austere economic plan due to projections pointing to a grave recession. This plan was largely unpopular even among supporters of the government, which, combined with increasing unemployment and inflation rates, curtailed support for the president both in Congress and society. To further weaken the government, the opposition introduced the 85/95 pension rule as an amendment to a bill that restricted eligibility to survivors pensions (PLV 4/2015). The 85/95 rule was projected to have a large negative impact on the government budget, since it increased early retirement pensions by an average of 30%, but it was very popular. Discussions in Congress effectively began in April 2015, and by June 17th the government caved in and adopted the new rule with Provisional Measure 676/2015, later converted into Law 13,183/2015 in November. Individuals who claimed their pensions a few months before June 2015, excluding the anticipatory period of April and May, had no reason to expect that a pension reform would take place and allow for a large benefit increase.

3.2 Data

I employ a novel administrative dataset of applicants of early retirement pensions issued by the Brazilian Social Security Agency (INSS) from 2012 to 2019, combined with labor market data to follow their formal employment trajectories. Additionally, I complement the analysis with a nationally representative survey of the Brazilian population above 50 years old.

3.2.1 Social security data

Social security benefits issued by the INSS are registered in the *Sistema Único de Informações de Benefícios* (SUIBE). I use both an unidentified and a semi-identified dataset from SUIBE containing all 2.7 million early retirement benefits issued from 2012 to 2019. In the unidentified version (SUIBE PDA) I am able to observe all relevant pension-related variables, such as dates of pension claiming and issuing, benefit size, and years of contribution, as well as key demographic characteristics (gender, date of birth, and municipality of residence). The semi-identified version (SUIBE LAI) contains the partial tax identification number[9] of all applicants (3 out of 11 CPF digits), but also has the full CPF for 21.1% of applicants, those whose pensions were issued in 2012 or 2013. Importantly, I also observe the gender, date of birth, and claiming date, which allows me to merge these datasets. Moreover, I use a public registry from INSS containing all social security offices in operation (*Perfil das Unidades*) and their opening dates to detect which municipalities had a field office each year.

3.2.2 Labor market data

I use the Brazilian employer-employee administrative records, the *Relação Anual de Informações Sociais* (RAIS). This dataset comes from the Ministry of Labor and allows me to recover detailed information on all labor contracts of formal workers for each year between 1985 and 2020. Not only

[9]The Brazilian tax identification number, known as CPF, uniquely identifies citizens across administrative records.

do I observe the full CPF of workers and the full tax identifier of firms, but I also have data on demographic characteristics (gender, race, date of birth, education) and labor market outcomes such as wage, occupation, municipality, firm sector, hire date, separation date, and firm's establishment date. Crucially, all firms are mandated by law to correctly provide this information, subject to fees.

3.2.3 Merge procedure and sample

Appendix Table D1 details the merge procedure adopted to create the SUIBE-RAIS sample. I employ a two-steps approach. First, I merge the unidentified and semi-identified versions of SUIBE using the gender, date of birth and date of claiming, restricting to the 1.9 million observations which are uniquely identifies by these variables.

Second, I merge the resulting SUIBE dataset to a cross-section of all individuals who appeared in RAIS from 2003 to 2020 using the partial CPF (the first two and the last digits), gender and date of birth. As expected, this procedure results is several non-uniquely identified matches. To overcome this issue, I leverage the facts that other covariates such as the municipality of residence are available in SUIBE and RAIS, and that the full CPF of 19.1% of pension applicants is available in the social security data. More specifically, I run a Logit model using this subset of 370 thousand individuals to predict which merges with partial CPFs are correct based on these covariates. The model performs very well in predicting correct merges, with an R-squared equal to 0.691 (see Appendix Table D2), allowing me to calculate the share of incorrect matches above a given cutoff for the predicted probability of being a correct merge (the error type I). Next, I merge this subsample from SUIBE with the RAIS cross-section using the full CPF to calculate the share of individuals that are excluded from the dataset when I restrict to observations above a given cutoff of this predicted probability (the error type II). Finally, the estimated coefficients from the Logit model are then used to perform an out-of-sample prediction for all matches using partial CPFs, where I choose a cutoff for the predicted probability of a correct merge that ensures a type I error of 5% and a type II error of 16.1% (see Appendix Figure D1).

The merged SUIBE-RAIS sample contains 1,304,360 early retirement applicants. I further restrict this sample to individuals who claimed pensions after January 2010 and had a high attachment to the formal sector[10] (see

[10]More specifically, I restrict the sample to workers who were employed in RAIS for at least 60 percent of the 10 years preceding their claiming month, and who had a private-sector formal job type (CLT contract) and were full-time workers (above 30 weekly hours) for at

Appendix Table D3 for a balance check). This restriction ensures that workers were not self-employed near their claiming period, which could hinder the correct prediction of their eligibility period to claim a pension. The final SUIBE-RAIS sample has 1,135,670 workers, for which I observe information on their retirement pension, as well as their formal labor market trajectories.

3.2.4 Survey data

I complement the administrative records with a nationally representative survey of the Brazilian population aged 50 years or older, the Brazilian Longitudinal Study of Aging (ELSI-Brazil) conducted by the Oswaldo Cruz Foundation. This survey adopts a framework similar to the Health and Retirement Study in the U.S. (Lima-Costa et al., 2017) and asks for detailed information on the aging process[11]. Particularly, respondents are asked about their health, assets and consumption levels, as well as demographics and work- and retirement-related information. Importantly, I employ the second wave of ELSI-Brazil, which was conducted from 2019 to 2021 and surveyed 9,949 individuals. In particular, I adopt this survey to analyze consumption levels of the population who was likely affected by the reform, and compare it to the overall population in order to implement the welfare analysis.

3.2.5 Summary statistics

Appendix Table C1 presents summary statistics for the main variables from ELSI-Brazil. Respondents are on average 63.3 years old and 41.5% report still being attached to the labor force, while 49.2% already receive an old-age pension. The mean household income is equal to R$2967.58, while household consumption equals R$1263.08. Finally, there is a lot of heterogeneity between early retirees and the overall population. Compared to the overall population, where 23.6% have secondary education and the mean pension size is R$1770.40, 35.8% of early retirees have completed high school, and their mean benefit size is R$2354.35. Additionally, only 16.9% of early retirees report having worked informally during their careers, whereas this share is 38.6% for the overall population.

Table 3.1 presents the summary statistics of the full SUIBE-RAIS sample. Most workers in this sample are men and white. Early retirement pension

least 20 percent of their employment period before claiming. See Appendix Figure D2 for descriptive statistics and additional details on the sample selection procedure.

[11]To the best of my knowledge, Banerjee et al. (2023) is the only other economics paper that leveraged this novel survey.

applicants are not representative of the average Brazilian worker, as being employed for 30 to 35 years in the formal sector, before the statutory retirement ages, is uncommon in a country with a large informal sector. This also rationalizes the high degree of education in the sample, where almost one-fifth have completed college and more than half have finished high school. For comparison, only 23.6% of the population aged 50 or above have secondary education according to ELSI-Brazil, and only 6.1% are college-educated.

The average claiming age of 54.4 years old is quite young but consistent with the lack of a minimum age to claim early retirement pensions in Brazil. Furthermore, the average period of pension deferral is over two years, but there is a high degree of dispersion. In fact, the median pension deferral is only 1.25 year, as highlighted in Appendix Table A1. The average monthly salary is equal to 4.46 minimum wages (from 2019) and the median is 2.57, which also indicates that early-retirees are better off financially than the average Brazilian. The average replacement rate is equal to 71.8% such that workers are heavily penalized by claiming their pension early. At last, the resulting monthly benefit is, on average, approximately 2.39 minimum wages, which is above the average per capita income of 1.44 minimum wages calculated by the Brazilian Institute of Geography and Statistics for 2019.

Table 3.1 also presents summary statistics for the main sample used in the empirical analyses, comprised of individuals most likely affected by the 2015 Reform. As discussed above, the 85/95 rule allowed workers to increase their pension by removing the *fator previdenciário* from the calculation of the benefit size. However, as social security benefits are capped on the lower end by the minimum wage, an individual whose average monthly salary is close to this value was already not affected by the discount factor before 2015, such that their behavior is unchanged. For this reason, I focus on the subset of workers whose average monthly salary was above 1.25 minimum wages.

In Figure 3.3, I plot the density of the sum of age and years of contribution at the time of claiming, pre- and post-reform. This figure presents clear evidence of bunching at the 85/95 cutoff as a result of the 2015 pension reform. Notably, the bunching is more pronounced for women, which is consistent with a higher replacement rate discontinuity at the cutoff for this group, as shown in Figure 3.2.

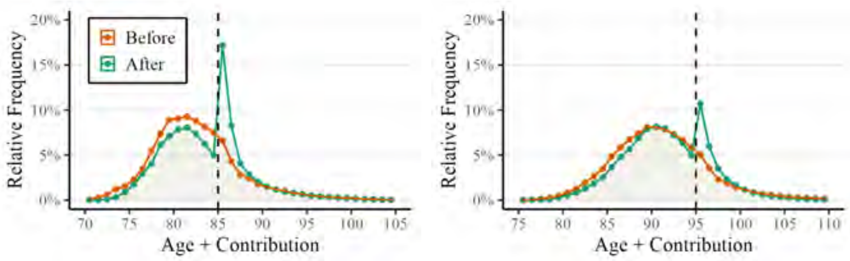
Table 3.1: Summary statistics

	Full sample		Main sample	
	Mean	SD	Mean	SD
A. *SUIBE-RAIS variables*				
Male	0.633	0.482	0.665	0.472
White	0.757	0.429	0.765	0.424
Completed high school	0.532	0.499	0.562	0.496
Completed college	0.183	0.386	0.204	0.403
Birth year	1960.888	5.120	1960.968	5.109
Claiming year	2015.317	2.303	2015.315	2.299
Age at eligibility	51.973	5.114	51.939	5.057
Age at claiming	54.422	4.786	54.343	4.781
Actuarial replacement rate	0.718	0.154	0.718	0.155
Benefit size (BRL 2019)	2385.163	1345.317	2553.184	1334.499
Years of contribution	34.892	3.520	35.137	3.462
B. *RAIS (2003-20) variables*				
Prob. employment	0.591	0.492	0.605	0.489
Monthly salary (BRL 2019)	3167.462	7139.332	3496.373	7520.012
Monthly salary (conditional)	5355.636	8629.171	5775.481	8958.241
Last year formally employed	2017.515	3.166	2017.686	3.006
Individuals	1,135,670		1,003,118	
Observations (RAIS 2003-20)	40,869,756		36,107,532	

Note: The table presents key summary statistics for the full sample and the main sample derived from SUIBE-RAIS. Panel A consists of cross-sectional variables, while Panel B are variables calculated in panel at the semester-year level from RAIS. See Appendix Table A1 for an expanded version of this table.

Figure 3.3: Bunching at the 85/95 cutoff generated by the 2015 Reform

A. For women **B.** For men



Note: This figure presents the relative frequency of claiming at each point (Age + Contribution) for women and men, both before and after the reform.

4
Effect on Pension Claiming

How much are people willing to postpone pension claiming after an increase in the return of deferral for further periods? In this section, I explore the policy discontinuity created by the 2015 Reform to answer this question by estimating the substitution elasticity of pension claiming with respect to financial incentives, $\varepsilon_{CH}^{t-\bar{t}}$, using a difference-in-bunching approach.

Previous research sought to estimate the price elasticity of claiming leveraging bunching at discontinuities in the severance pay schedule (Manoli and Weber, 2016), reform-based approaches (Lalive et al., 2023) and survey-experimental evidence (Glenzer et al., 2024), and has predominantly found that workers are not very responsive to financial incentives of deferral. However, there are two main limitations to these findings. First, prior work has mostly explored contexts where these financial incentives are not very sizable, or where policy changes do not produce very large deferral incentives. Manoli and Weber (2016) overcomes this issue by exploring the Austrian context, where the size of severance payment workers are eligible to claim once they retire changes discontinuously depending on their tenure. The limitation is that claiming and labor market exit are coupled in their context. Workplace-level behavior has been documented to affect the timing of retirement (Deshpande et al., 2024), such that frictions affecting this decision might impact the estimate of their elasticity.

Second, given that benefit schedules are usually a function of age, estimates stemming from policy changes to such schedules could be influenced by reference-dependence. Seibold (2021) shows that statutory retirement ages play a key role in explaining the patterns of pension claiming and retirement, and that this can be rationalized in a model with reference-dependent behavior.

The Brazilian setting is uniquely suited to estimate the pension claiming elasticity due to the fact that I can overcome both of these limitations. Figure 3.2 depicts the benefit schedule before and after the 2015 Reform. The pension increase at the discontinuity is of 20% for men and 35% for women, on average, such that financial incentives are sizable. Reference-points are also not a concern in the Brazilian context, as eligibility to early retirement pensions does not depend on statutory ages from the pension schedule. Furthermore, the threshold of age and years of contribution at which the worker qualifies to the 85/95 rule was, in practice, individual-specific, as it depends on her age when she became eligible to an early retirement pension, which is a continuous variable. Hence, the bunching observed in Figure 3.3 can be confidently interpreted as a reaction to the financial incentives generated by the pension reform, rather than to reference-points.

Next, I present the framework for the substitution elasticity of pension claiming with respect to benefits, and discuss its estimation in the empirical strategy subsection.

4.1 Framework

I adapt the framework for the elasticity of participation with respect to the change in financial incentives from Manoli and Weber (2016)[1] to my context. Their framework is based on the comparison of the probability distribution of labor force participation when there is a discontinuity in the benefit schedule at a given cutoff $\bar{t}$ to the counterfactual distribution that would have been observed had the pension schedule been linear. In my framework, I leverage the fact that there was a policy change, such that the distribution prior to the reform can be observed.

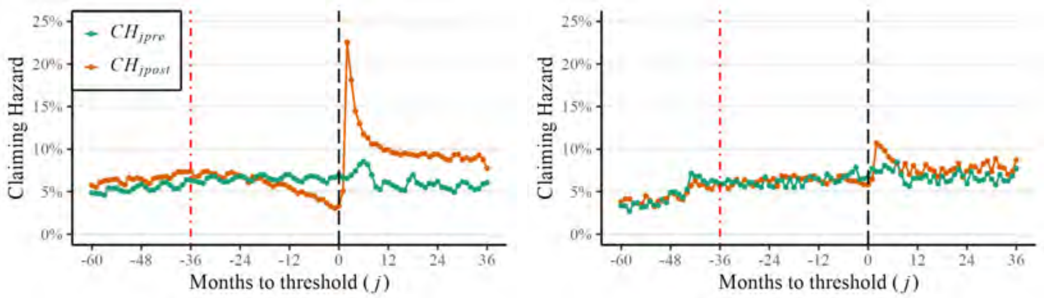
I denote the claiming hazard for month $j \equiv t - \bar{t}$ relative to the cutoff as $CH_{j,p}$, where $p \in \{pre, post\}$ indicates the timing relative to the reform. The claiming hazard is the probability that a worker claims her pension at month j conditional on being eligible and not having claimed yet. Figure 4.1 Panel A presents the claiming hazard both before and after the reform. As expected, $CH_{j,pre}$ is smooth across the threshold $\bar{t}$, while $CH_{j,post}$ is decreasing in j until $\bar{t}$, and jumps discontinuously after the threshold. This is the case since the financial incentives of deferring the claim until $\bar{t}$ were changed after 2015. Therefore, I define the substitution elasticity of pension claiming deferral with respect to financial incentives as the percentage change in claiming deferral divided by the percentage change in financial incentives, which I allow to differ for each period j before the cutoff.

Given the claiming hazard for month $j < 0$ relative to the 85/95 threshold after the reform ($CH_{j,post}$) and the counterfactual claiming hazard had the reform not taken place ($CH^c_{j,post}$), I follow Manoli and Weber (2016) and define the change in pension claiming deferral as:

[1] In particular, the authors estimate an elasticity of participation with respect to pension benefits by exploiting notches of severance payment at certain life tenures for Austrian workers considering retirement.

Figure 4.1: Claiming hazard $CH_{j,p}$ before and after the 2015 Reform

A. Main sample **B.** Minimum-wage earners



Note: This figure plots the claiming hazard for the main sample and for the minimum-wage earners sample by distance to the 85/95 threshold. To calculate the claiming hazard, I create a panel where each individual appears from the month of eligibility to the month of claiming. I restrict to observations after 2011 and separate between before and after the 2015 Reform. I impute zeros to all observations excluding the claiming month, which is set to one. Then, take the average across individuals for each distance to 85/95.

$$\Delta\% CH_j \equiv \frac{CH_{j,post} - CH^c_{j,post}}{CH^c_{j,post}} \tag{4-1}$$

Similarly, let $b(j)$ be the pension schedule for month $j < 0$ relative to the 85/95 threshold post-reform and $b^c(j)$ the benefit size had the reform not taken place. Before the reform, the financial incentive of deferring the claim from j until $\bar{t}$ was equal to $b^c(1) - b^c(j)$, while after the reform it became $b(1) - b(j)$. As $b(j) = b^c(j)$, the change in financial incentives is given by:

$$\Delta\% b_j \equiv \frac{\left[b(1) - b(j)\right] - \left[b^c(1) - b^c(j)\right]}{b^c(1) - b^c(j)} = \frac{b(1) - b^c(1)}{b^c(1) - b(j)} \tag{4-2}$$

which is the change in benefits due to the reform upon reaching the 85/95 threshold, relative to the increase in benefits from deferring for $j + 1$ periods before the reform.

Moreover, I leverage the large notch in the benefit schedule to recover the structural elasticity of claiming (Kleven and Waseem, 2013). In a frictionless world, claiming just one month prior to the 85/95 cutoff would entail an opportunity cost that arguably could not be rationalized by any intertemporal discount factor. In fact, a very conservative calculation points to a discontinuity of at least R$42,000 in present discounted value terms at the threshold, such that the monthly discount factor that rationalizes claiming at $j = -1$ would be as low as $\beta = 0.77$[2]. Thus, I follow Manoli and Weber (2016) and make the assumption that the share of individuals constrained by frictions in their

[2]More specifically, I consider an increase of 30% to a monthly pension of R$1,000 paid over 15 years with an annual real interest rate equal to 3%. By claiming at $j = -1$, the PDV of the pension stream equals 143 thousand BRL, while deferring the claim until $j = 0$ entails a PDV equal to 186 thousand.

claiming decision in all periods $j < -1$ is equal to the share of workers who claim just one month before the 85/95 threshold post-reform, relative to the counterfactual: $\kappa \equiv CH_{j=-1,post}/CH^c_{j=-1,post}$.

Therefore, I define the structural elasticity of pension claiming deferral as $\Delta\%CH_j/\Delta\%b_j$ divided by the share of individuals who are unconstrained in their claiming decision, $1-\kappa$[3]. Hence, the substitution elasticity of pension claiming with respect to financial incentives is simply its negative:

$$\tilde{\varepsilon}^j_{CH} \equiv -\frac{\Delta\%CH_j/(1-\kappa)}{\Delta\%b_j} \tag{4-3}$$

4.2 Empirical strategy

The estimation of ε^j_{CH} depends on a credible identification of the counterfactual claiming hazard, $CH^c_{j,post}$. I estimate this counterfactual using a difference-in-bunching estimator (Kleven, 2016).

Kleven and Waseem (2013) show that elasticities under notched budget sets can be estimated by backing out the missing mass from the bunching mass to determine the marginal buncher, under the assumption that bunchers come exclusively from a continuous set below/above the cutoff. However, the notch in the lifetime budget constraint of workers induced by the 2015 pension reform creates a bunching mass originated from both sides of the cutoff, given that the pension schedule becomes flat past the 85/95 cutoff, as depicted in Figure 3.2. This feature violates the assumption adopted in Kleven and Waseem (2013). Hence, the difference-in-bunching design allows for a more credible estimation of the counterfactual claiming hazard distribution than a regular bunching estimator.

I exploit the fact that I observe the pre- and post-reform claiming hazards to create the counterfactual distribution, as presented in Figure 4.1. The difference-in-bunching approach uses the distribution observed before a policy change to create a counterfactual distribution for the post-reform period (Bäckman et al., 2024). In addition to not relying in the assumption of a continuous set of bunchers below the cutoff, this approach also addresses recent criticisms to the parametric assumptions from conventional bunching estimators (Dube et al., 2020). The counterfactual distribution is obtained from:

[3]An alternative definition for the elasticity of pension deferral with respect to benefits would be just $\varepsilon^j_{CH} \equiv \Delta\%CH_j/\Delta\%b_j$, which is the change in deferral divided by the change in financial incentives. However, this "naive" elasticity does not take into account the possibility that individuals might be constrained in their decision to defer. A possible reason why this happens is lack of knowledge about such financial incentives.

$$CH_{j,p} = \sum_{i=1}^{F} \beta_i (z_{jp})^i + \alpha 1(p = post) + \sum_{p \in \{pre,post\}} \sum_{k \geq \pi_L} \gamma_{jp} 1(z_{jp} = k) \times 1(p = post) + \epsilon_{jp} \tag{4-4}$$

where $CH_{j,p}$ is the claiming hazard for workers that claim j months relative to the threshold and do so before ($p = pre$) or after ($p = post$) the reform. F is order of the polynomial, and z_{jp} denotes months to the threshold in bin $j \times p$ for $j \in \{-60, ..., 36\}$ and $p \in \{pre, post\}$. π_L corresponds to the first month relative to the threshold in which the claiming hazard is affected by the financial incentives introduced by the reform. Thus, the counterfactual claiming hazard is estimated as $\widehat{CH}^{c}_{j,post} = \sum_{i=1}^{F} \hat{\beta}_i (z_{jp})^i + \hat{\alpha}$

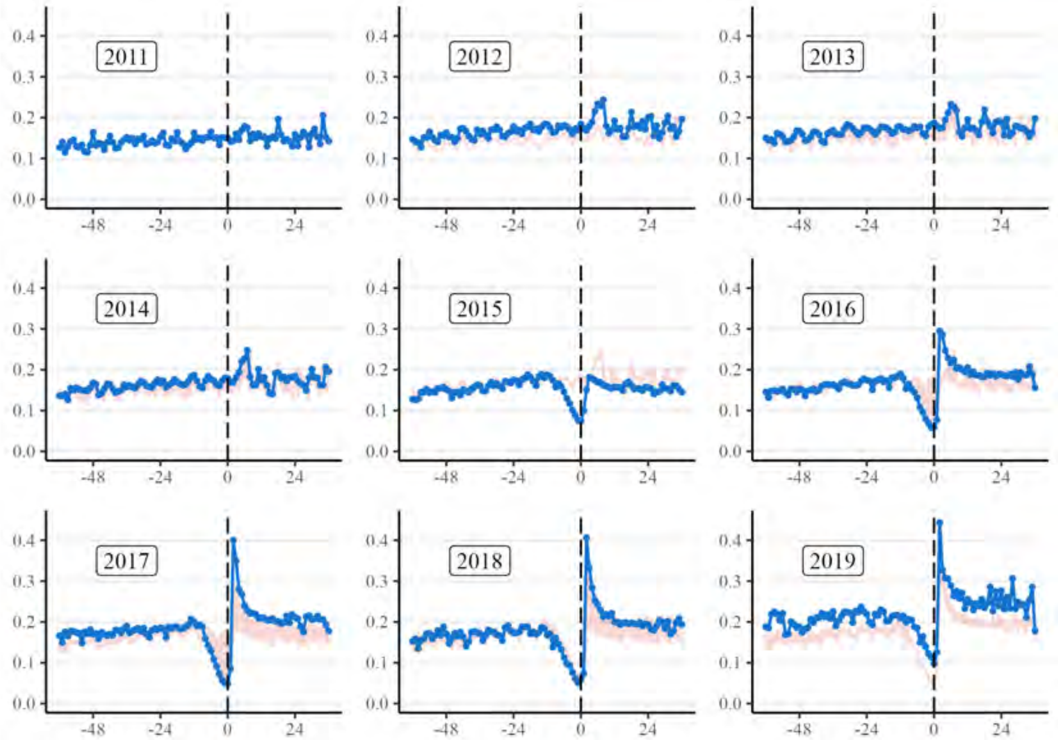
4.2.1 Identifying assumption

The identifying assumption is that, in the absence of the reform, the claiming hazard near the threshold (i.e., in the excluded range) would have evolved in parallel with the claiming hazard far from the cutoff. Although this is an untestable assumption, there is suggestive evidence that it is valid. First, the 85/95 threshold is exogenous to any individual behavior prior to the reform. The sum of age and years of contribution was not relevant for any other policies before 2015. Second, there are no other policy changes affecting the pension schedule of early retirement pensions during this period. Figure 4.2 presents the evolution of the claiming hazard across the years and, reassuringly, changes started to show up only after 2015. Third, I show that the pre- and post-reform claiming hazards follow a similar trend for months far from the 85/95 threshold.

To further assess validity, I check in Figure 3.1 Panel B how the claiming hazard distribution evolved for a sample of individuals who should not respond as much to the 2015 pension reform, the minimum-wage earners[4]. There are no systematic differences in their claiming hazard after the reform, which is reassuring. Appendix Figure A1 shows the counterfactual derived from estimating Equation 4-4 in the minimum-wage earners sample. The results suggest that the difference-in-bunching specification performs very well in estimating the post-reform distribution for these workers near the cutoff.

[4]Workers with an average monthly wage close to the lower cap of retirement pensions, the minimum wage, were not discounted by claiming their pensions early, both before and after the reform. Thus, their pension schedule was unchanged after 2015 such that I can test if the identifying assumption holds in their case.

Figure 4.2: Evolution of the claiming hazard $CH_{j,y}$ across the years $y \in \{2011, ..., 2019\}$



Note: This figure plots the claiming hazards for each year from 2011 to 2019, for each month relative to the 85/95 threshold. For each year y, I keep only those individuals who claimed at that year and calculate for each month relative to the 85/95 threshold the probability of claiming, conditional on being eligible. I also present in light red the claiming hazard from the previous 3 years for comparison.

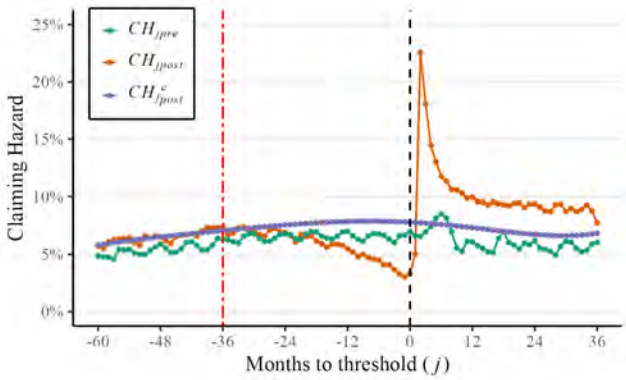
4.3 Results

Figure 4.3 presents the estimated counterfactual using the difference-in-bunching approach from Equation (4-4). I use the main sample an assume a fifth-order polynomial ($F = 5$) and that individuals debating whether to claim their pensions within a distance of three years relative to 85/95 threshold are not affected by the cutoff ($\pi_L = -36$).

The results for the change in financial incentives, the change in pension claiming deferral, and the estimated substitution elasticities for several months j relative to the threshold are shown[5] in Table 4.1 and Appendix Figure A2. I estimate that $\hat{\kappa} = 0.39$ and calculate standard errors as the standard deviation of bootstrapped replications, following Manoli and Weber (2016). The estimated distribution of pension claiming elasticities ranges from -0.217, for 10 months before $\bar{t}$, to -0.061, for 35 months before the threshold. As the threshold approaches, financial incentives increase faster than pension claiming

[5]Appendix Table A2 presents the results for all periods.

Figure 4.3: Difference-in-bunching strategy – Counterfactual claiming hazard $\widehat{CH}^{c}_{jp}$



Note: This figure presents the results from the difference-in-bunching strategy to create a counterfactual claiming hazard using Equation (4-4). The red dotted line represents $\pi_L = -36$, and I use a fifth order polynomial $F = 5$.

deferral such that the estimated elasticities are smaller. The average elasticity from -35 to -1 is -0.098[6], or -0.132 when I consider only the year preceding the 85/95 cutoff. This estimate implies that a 10 percent increase in benefits from further deferral reduces the probability of workers claiming their pensions one year before by 1.32 percent, on average.

These results are in line with previous research. Manoli and Weber (2016) estimate a distribution of elasticities ranging from -0.28 to -0.14, while Seibold (2021) estimates an elasticity of pure financial incentives of -0.08. Glenzer et al. (2024) estimates a claiming elasticity of -0.111 using a survey design and of -0.156 leveraging a Canadian pension reform. Overall, my findings are consistent with the recent literature pointing out that pension claiming behavior is rather inelastic to financial incentives.

4.3.1 Robustness

I perform several robustness checks by changing either the threshold π_L or the polynomial order F considered in the estimation of Equation 4-4. Appendix Table E1 and Appendix Figure E1 present the results. The estimated average elasticity of claiming one year before the threshold is consistent among various specifications and ranges from -0.118 to -0.133. Likewise, the share of constrained individuals ranges from 0.388 to 0.405. I interpret this as evidence that my results are robust to changes in the excluded range and order of the polynomial employed in the estimation.

[6] I calculate the weighted average for elasticities from -35 to -1. The weights are the number of individuals eligible to claim the pension at each month j relative to the threshold.

Table 4.1: Substitution elasticity of pension claiming – Summary of results

Months to threshold	-35	-30	-25	-20	-15	-10	-5	-1	Mean		
									-36	-24	-12
A. ***Change in financial incentives***											
$\Delta\%b_j$	1.649	1.952	2.246	2.771	3.762	4.826	12.346	47.315	6.965	9.211	14.926
B. ***Change in pension claiming deferral***											
$\Delta\%CH_j$	0.061	0.030	0.076	0.171	0.325	0.639	0.932	1.567	0.402	0.564	0.864
	(0.015)	(0.016)	(0.017)	(0.019)	(0.021)	(0.026)	(0.031)	(0.041)			
$\Delta\%CH_j/(1-\kappa)$	0.100	0.050	0.125	0.280	0.532	1.047	1.527	2.567	0.659	0.925	1.416
	(0.023)	(0.025)	(0.027)	(0.029)	(0.030)	(0.033)	(0.035)	(0.041)			
C. ***Substitution Elasticities of Pension Claiming***											
$\varepsilon^j_{CH} = -\frac{\Delta\%CH_j}{\Delta\%b_j}$	-0.037	-0.016	-0.034	-0.062	-0.086	-0.132	-0.075	-0.033	-0.060	-0.078	-0.081
	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)	(0.002)	(0.001)			
$\tilde{\varepsilon}^j_{CH} = -\frac{\Delta\%CH_j/(1-\kappa)}{\Delta\%b_j}$	-0.061	-0.025	-0.056	-0.101	-0.141	-0.217	-0.124	-0.054	-0.098	-0.128	-0.132
	(0.014)	(0.013)	(0.012)	(0.010)	(0.008)	(0.007)	(0.003)	(0.001)			

Note: This table presents a summary for the estimated substitution elasticity of pension claiming with respect to financial incentives, defined in Equation (4-3) and estimated using the difference-in-bunching strategy laid out in Section 4.2. See Appendix Table A2 for a full table with elasticity for all periods and Appendix Figure A2 for an illustration.

4.3.2 Heterogeneity

Appendix Table F1 and Appendix Figure F1 present the results of various heterogeneity analyses by gender, earnings, schooling etc. First, women have an average elasticity (1 year before $\bar{t}$) of -0.112, while men of -0.127. This is the case as, although women face higher financial incentives, their change in pension deferral is proportionately smaller than men's. Compared to nonwhite individuals, white workers in the main sample are more responsive to financial incentives of deferral, with an average elasticity of -0.137 compared to -0.12. Additionally, there is considerable heterogeneity by labor earnings and education level. Individuals with higher earnings[7] have an average elasticity of -0.165, compared to -0.091 for low earnings workers. Those who completed college are twice as responsive as those who did not complete high school, with average elasticities of -0.177 and -0.089, respectively. I do not find relevant heterogeneity between individuals with good and bad health[8], but those in good health are slightly more sensitive. Finally, white collar workers are more sensitive than their blue collar counterparts, with average elasticities of -0.142 and -0.092.

[7] Which I define as being above the median average earnings within my full sample.

[8] I proxy for health using the sick leave variable present in RAIS. An individual is assumed to have bad health if she was on sick leave at least once in RAIS.

5 Effect on Labor Market Exit

To what extent do people change their early retirement decision due to an unexpected increase in social security benefits? In this section, I answer this question by leveraging plausibly exogenous variation in the benefit size of workers induced by the lack of anticipation of the 2015 pension reform. More specifically, I estimate the income elasticity of labor market exit with respect to benefit size, $\eta_S^{t-\kappa}$.

The income effect of government transfers on labor supply is crucial for the policy evaluation of social insurance programs, old-age retirement benefits and survivors' pensions schemes. However, credibly identifying this parameter is challenging, as the ideal setting should satisfy two conditions (Danzer, 2013). First, it requires a large change in benefit levels which is not anticipated by workers and neither fully determined by individual choices. Second, the benefit schedule should not allow those affected by the policy change to adjust their pensions through other decisions which could introduce substitution or option-value effects. It has proven difficult to find settings that meet these requirements.

Giupponi (2024) has recently been able to overcome these identification challenges by exploring the context of survivors' pensions in Italy, where a policy change created a sizable decrease in the pension size of workers depending on the date of spousal death. The results suggest large income effects which are partially driven by delayed retirement, with a marginal propensity to earn out of unearned income of -0.8. In the case of old-age retirement benefits, Danzer (2013) estimates the income effect by leveraging an unanticipated pension reform in Ukraine which doubled the minimum benefit, and finds an income elasticity of retirement of 0.1-0.2. Moreover, de Carvalho Filho (2008) explores a pension reform to old-age benefits in rural Brazil and finds even larger income effects, with an elasticity of labor force non-participation with respect to benefit size equal to 0.8.

In theory, it is not clear that the income effect should operate the same way in the context of early retirement benefits. These workers might claim their pensions early and subject to non-actuarially fair deductions because they are facing liquidity constraints and higher risks of job displacement[1] (Kruse and Myhre, 2023). If liquidity constraints are a more relevant issue for these individuals, we should expect a greater reduction in labor force participation after an increase in their benefit size, driven by the income effect. Furthermore, if this group faces an elevated risk of job displacement, then dynamic considerations to the income effect might be relevant, as a larger pension would decrease job search costs and could lead to a transient reduction in labor supply followed by a surge in participation.

Below, I discuss the empirical strategy used to estimate the income elasticity of labor market exit in the context of early retirement benefits using the variation introduced by the 2015 Reform.

5.1 Empirical strategy

I use an instrumental variables approach to uncover the income elasticity of retirement and compare the labor force participation of workers from the main sample who claimed their pension shortly after June 17th 2015 ($Z_i = 1$) to those who claimed narrowly before ($Z_i = 0$), leveraging the fact that the 2015 pension reform was unanticipated. More specifically, I run dynamic difference-in-differences models to assess the reduced-form effect of the reform on employment and the first-stage effect on the benefit replacement rate. The control group $Z_i = 0$ consists of individuals who claimed their pension from July 1st 2014 to May 17th 2015, and the treatment group $Z_i = 1$ are those who claimed from July 17th 2015 to December 31st 2015. Lastly, I compute an elasticity of labor supply as the reduced-form effect divided by the first-stage effect for each period after claiming.

As discussed above, the variation induced by the 2015 Reform will identify an income effect as long as it has generated a benefit increase which is not anticipated nor fully determined by workers and if there are no incentives in the benefit schedule that could introduce substitution effects into the labor supply response to the policy change. Appendix Figure A3 illustrates Google Trends searches for retirement-related terms in Brazil. Consistent with the no-anticipation assumption, searches suddenly spike only at the week of the Reform, after a brief period of anticipation starting in May 2015. Appendix Figure A5 presents descriptive statistics for individual characteristics by claiming week relative to the Reform. Reassuringly, individual characteristics are balanced for weeks before the reform. Therefore, the first requirement

[1]Kolsrud et al. (2024) show that the consumption of early retirees is lower than that of late retirees, and that they face a higher drop in consumption upon retirement.

that the benefit change is unexpected seems valid in this context. As the benefit schedule becomes flat upon reaching 85/95 points, the second requirement should also be valid as long as the change in claiming behavior in order to qualify for the pension increase affects the labor supply decision only through the higher replacement rate, such that there are no substitution effects.

Nonetheless, while the reform was not anticipated, it is still the case that workers who claimed their pensions pre-reform are slightly different from those who claimed it after the reform, as shown in Table 5.1. Therefore, I adopt an inverse probability weighting scheme to ensure balance between pre- and post-reform pension claimants[2], and run the following reduced-form and first-stage regressions:

$$y_{iq} = \alpha_i + \theta_q + \tau_{y(q)} + \sum_{q \neq -1} \beta_q^{RF} \cdot D_{iq}^k + \epsilon_{iq} \tag{5-1}$$

$$b_{iq} = \alpha_i + \theta_q + \tau_{y(q)} + \sum_{q \neq -1} \beta_q^{FS} \cdot D_{iq}^k + \epsilon_{iq} \tag{5-2}$$

[2]I predict the probability that a worker in this sample claimed the pension after the reform using a Logit model with controls such as gender, year of birth, education, race, municipality, and most common occupation and firm sector. Appendix Figure A4 depicts the density of the propensity scores of both types of workers.

Table 5.1: Summary statistics: $Z_i = 0$ and $Z_i = 1$

	Without IPW			With IPW		
	$Z_i = 0$	$Z_i = 1$	Diff.	$Z_i = 0$	$Z_i = 1$	Diff.
Male	0.686	0.664	-0.022***	0.665	0.664	-0.002
Completed High school	0.533	0.562	0.029***	0.562	0.562	0.000
Completed College	0.184	0.209	0.025***	0.208	0.209	0.001
White	0.765	0.759	-0.006**	0.759	0.759	0.000
Birth year	1960.236	1960.439	0.203***	1960.446	1960.439	-0.007
Avg. earnings	4832.884	5050.980	218.095***	5002.326	5050.980	48.653
Years of contribution	35.232	35.440	0.208***	35.079	35.440	0.361***
Age at claiming	54.194	54.828	0.634***	53.987	54.828	0.841***
Age + Years of contribution	89.407	90.269	0.862***	89.044	90.269	1.225***
Pension deferral (years)	2.299	2.656	0.357***	2.235	2.656	0.421***
Eligible to 85/95	0.294	0.435	0.141***	0.289	0.435	0.146***
Benefit size (BRL 2019)	2403.458	2736.162	332.704***	2412.578	2736.162	323.585***
Actuarial Replacement rate	0.720	0.740	0.020***	0.711	0.740	0.028***
Actual Replacement rate	0.679	0.742	0.063***	0.667	0.742	0.075***
Benefit issued in 1st quarter	0.370	0.182	-0.188***	0.379	0.182	-0.198***
Employed in baseline	0.861	0.844	-0.017***	0.865	0.844	-0.021***
Log Income in baseline	8.055	7.892	-0.162***	8.114	7.892	-0.221***
Prob. employment after claim	0.554	0.533	-0.022***	0.562	0.533	-0.029***
Log Income after claim	8.920	8.964	0.044***	8.965	8.964	-0.001
No. Individuals	96,844	64,127				
Observations	2,033,724	1,346,667				

Note: This table presents summary statistics for the control ($Z_i = 0$) and treatment ($Z_i = 1$) groups. The first consists of workers who claimed their pensions from July 1st 2014 to May 17th 2015, while the second are those who claimed from July 17th 2015 to December 31st 2015. The first two columns present raw averages, while the last two columns are averages weighted by inverse probability weights. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

where y_{iq} is a dummy variable of formal employment for worker i in quarter $q \equiv t - \kappa$ relative to the claiming period, b_{iq} is the replacement rate of the pension which I set to zero until benefit issuance, and $D^k_{iq} = Z_i \times \mathbb{1}(q - \kappa = k)$ indicates whether period q is exactly k quarters after the claiming period κ for individual i. The specifications include individual fixed-effects α_i to account for time-invariant unobservables at the worker level, distance to claiming fixed-effects θ_q which capture time-variant changes in employment as pension claiming approaches and calendar-year fixed-effects $\tau_{y(q)}$.

I define the second-stage effect for quarter $q > 0$ after the reform as the reduced-form divided by the corresponding first-stage coefficient relative to its baseline such that $\hat{\beta}^{SS}_q \equiv \frac{\hat{\beta}^{RF}_q}{\hat{\beta}^{FS}_q/\bar{b}}$. Finally, the elasticity of labor market exit η^q_S in quarter q is given by the (negative of the) second-stage coefficient divided by the employment baseline in $q = -1$. I estimate $\eta^q_S \equiv -\hat{\beta}^{SS}_q/\bar{y}_{-1}$ using a bootstrap procedure where I run Equations (5-1) and (5-2) in bootstrap samples and calculate η^q_S for each replication.

5.1.1
Identifying assumption

The identifying assumptions for the IV approach are the relevance and exogeneity of the instrument. After the reform, workers were able to claim a much higher pension through the 85/95 rule such that post-reform claiming most likely impacts the probability of formal employment for people close to retirement. Moreover, the F-statistic of the first-stage equals 6,886.06 and is large enough to reduce concerns regarding the relevance of this instrument, as presented in Table 5.2. As for exogeneity, workers should not be able to self-select into claiming in the pre- and post-reform periods in order to qualify for the 85/95, to the extent that they would have followed parallel trends had the policy change not occurred. This assumption should hold as the 2015 Reform was not anticipated and because I only consider workers in a narrow window around the reform period, excluding those in a 2-months interval. As shown in Appendix Figure A6, there are no systematic pre-trends between $Z_i = 0$ and $Z_i = 1$, which supports the validity of this assumption. Additionally, this variation will isolate the income effect provided that employment in the post-reform period is influenced by changes in claiming behavior solely through the increase in the benefit size.

Importantly, in the first post-reform quarters the impact of claiming after the reform is most likely positive due to the fact that higher demand led the INSS to delay the analysis and dispatch of new requests of retirement pensions. In fact, 37% of individuals who claimed their pension prior to the reform already had their pensions issued by the first quarter after claiming, compared to 18% for the treatment group. However, this difference stabilizes by the third quarter after claiming such that it should not affect estimates in the medium-term.

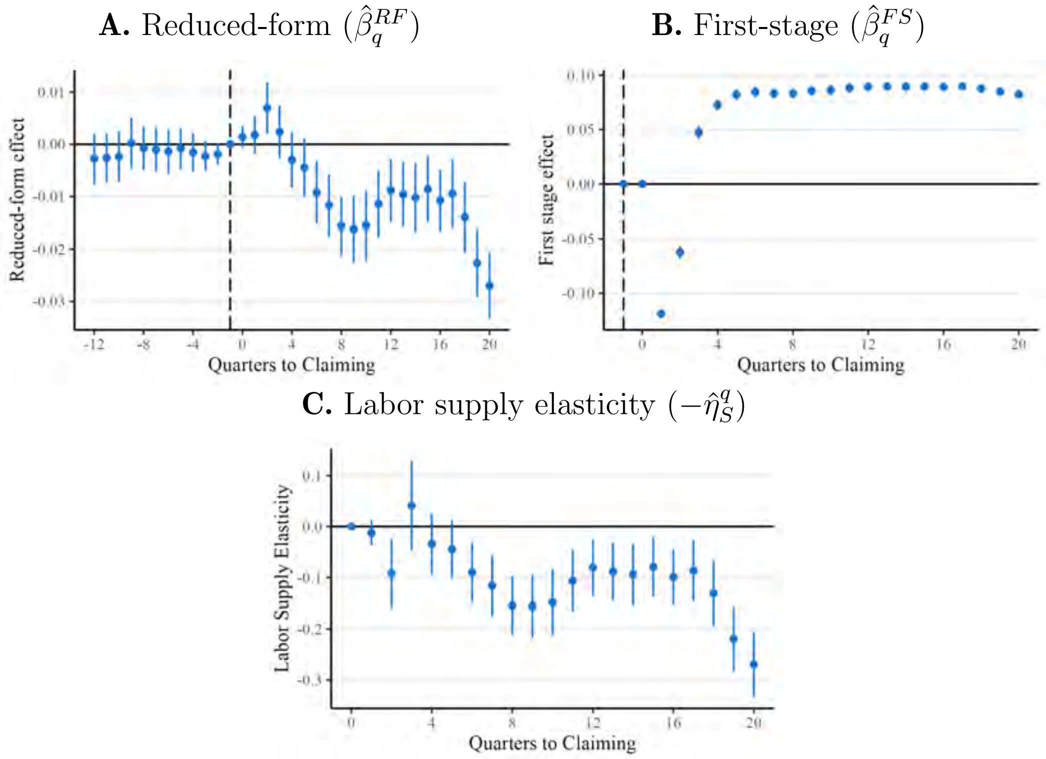
5.2 Results

Figure 5.1 and Table 5.2 present the empirical results. Two years after claiming, the reform had a negative and statistically significant reduced-form effect of -1.8% relative to the baseline, which increases to -3.1% after five years. Note that there is an adjustment period in the first two years after claiming, as the probability of employment drops sharply at first, then gradually rises by the third year. The first-stage effects point to a much higher replacement rate for those who claimed their pensions after the reform, with an increase of 9 p.p., on average. As expected, the first-stage effect is negative in the first two quarters after claiming, as individuals in the treatment group had a slower benefit issuance process. At last, the income elasticity of retirement follows a similar trend to the reduced-form effect, and equals 0.155, 0.081, and 0.270 by the end of years 2, 3 and 5 since claiming, respectively.

I also present the results for the reduced-form and first-stage effects for a traditional TWFE estimator, where I run Equations (5-1) and (5-2) for the whole sample. Appendix Table A3 and Appendix Figure A7 showcase the results. Reassuringly, the results hold up to the more conventional estimator as well. Furthermore, I report the results of the event-study for additional outcomes, namely the log of total income, the log of benefit size and the log of labor earnings. The results are shown in Appendix Table A4 and Appendix Figure A8. In line with the reduced-form and first-stage effects, there is a decrease in the log of labor earnings and a sharp rise of 17.2% in overall income two years after claiming, as the benefit increase offsets the drop in labor earnings.

In spite of the theoretical considerations that the income effect might operate in a distinct way in the context of early retirement, my results for the income elasticity of retirement are aligned with previous evidence. Compared to Danzer (2013), I also find that the income elasticity of retirement is in the range of 0.1-0.2, although by 5 years after claiming it surges to 0.27. I interpret this as evidence that liquidity constraints are not a main driver of early retirement requests in my sample. This is consistent with these workers being better off than the average Brazilian retiree, as they are more educated and have higher earnings (see Table 3.1). Nevertheless, my findings are consistent

Figure 5.1: Reduced-form effect, first-stage effect, and Income elasticity of labor supply



Note: This figure presents the results for the reduced-form and first-stage effects which I estimate using Equations (5-1) and (5-2) in bootstrap samples with replacement. Panel C depicts the resulting income elasticity of labor supply for each period relative to claiming. I present 95% confidence intervals along with point estimates for each semester, where standard errors are derived from the standard deviation of 100 bootstrap replications.

with a higher risk of job displacement for these individuals. The fact that the effect on employment goes through an adjustment period in the medium-run is consistent with a decrease in job search costs due to larger pensions, allowing these workers to change employers to avoid job displacement.

5.2.1 Robustness

I perform some robustness exercises where I use a shorter window around the reform period to define $Z_i = 0$ and $Z_i = 1$, where I run Equations (5-1) and (5-2) without inverse probability weights and where I run these Equations with a rich set of controls instead of the individual fixed-effects. For the first set of robustness checks, I define two alternative windows around the reform period. First, I consider $Z_i = 0$ as individuals who claimed their pensions starting in October 1st 2014, rather then July 1st 2014, while $Z_i = 1$ is unchanged. Next, I keep this smaller control group and restrict $Z_i = 1$ to individuals who claimed their pension until October 31st 2015, in place of December 31st 2015. For the last exercise, I control for microregion of residency, birth year, gender, schooling, race and affiliation type. The results are in Appendix Figure E2 and Appendix Table E2. The empirical results are quite robust to changes in the treatment assignment windows, as well as dropping the IPW. However, they are less robust to excluding individual fixed-effects in the regression. Hence, it might be the case that there are unobservable characteristics of these workers that the rich set of controls could not properly isolate. Nonetheless, I interpret this as evidence that the income elasticity of retirement is robust to changes in the sample construction and weighting scheme.

5.2.2 Heterogeneity

Appendix Table F2 presents the results for several heterogeneity analyses of the income elasticity of labor supply. I separate my sample by gender, good and bad health and educational attainment. I find that men are more responsive than women in the short- and long-terms, but confidence intervals overlap such that there is no compelling evidence for heterogeneity[3]. Likewise, there is no evidence of heterogeneity by health status. Finally, there are important differences by schooling level. In fact, the income elasticity of retirement for those who attended college is not statistically different from zero in any period at all, while the results are similar between those who did not complete high school and those who completed but did not go to college. This is consistent with Danzer (2013), who also finds that the less educated are more responsive to increases in the benefit size, given that the opportunity cost of foregone labor income is higher for the more educated.

[3]The one exception is the elasticity in the last period, where men are more than twice as responsive. However, this could be driven by the fact that men are eligible to early retirement pensions at an older age than women.

Table 5.2: Reduced-form effect, first- and second-stage effects and elasticity of labor supply

Quarters to claim (k)	Reduced-form (β_k^{RF})	First-stage (β_k^{FS})	Second-stage (β_k^{SS})	Elasticity ($-\eta_S^q$)
-12	-0.003 (0.003)			
-11	-0.003 (0.002)			
-10	-0.002 (0.002)			
-9	0.000 (0.002)			
-8	-0.001 (0.002)			
-7	-0.001 (0.002)			
-6	-0.001 (0.002)			
-5	-0.001 (0.002)			
-4	-0.002 (0.002)			
-3	-0.002 (0.001)			
-2	-0.002 (0.001)			
0	0.001 (0.001)	0.001 (0.000)***	0.777 (0.651)	0.910 (0.762)
1	0.002 (0.002)	-0.119 (0.002)***	-0.011 (0.011)	-0.012 (0.013)
2	0.007 (0.003)**	-0.062 (0.003)***	-0.079 (0.029)***	-0.092 (0.034)***
3	0.002 (0.003)	0.047 (0.003)***	0.035 (0.039)	0.041 (0.045)
4	-0.003 (0.003)	0.073 (0.003)***	-0.029 (0.026)	-0.034 (0.031)
5	-0.004 (0.003)	0.082 (0.002)***	-0.038 (0.025)	-0.045 (0.029)
6	-0.009 (0.003)***	0.085 (0.002)***	-0.077 (0.026)***	-0.090 (0.030)***
7	-0.012 (0.003)***	0.083 (0.002)***	-0.099 (0.026)***	-0.116 (0.030)***
8	-0.016 (0.003)***	0.083 (0.002)***	-0.132 (0.025)***	-0.155 (0.029)***
9	-0.016 (0.003)***	0.086 (0.002)***	-0.133 (0.027)***	-0.156 (0.032)***
10	-0.016 (0.003)***	0.087 (0.002)***	-0.127 (0.028)***	-0.148 (0.033)***
11	-0.011 (0.003)***	0.089 (0.002)***	-0.091 (0.026)***	-0.106 (0.031)***
12	-0.009 (0.003)***	0.089 (0.002)***	-0.069 (0.024)***	-0.081 (0.028)***
13	-0.010 (0.003)***	0.090 (0.002)***	-0.075 (0.025)***	-0.088 (0.029)***
14	-0.010 (0.003)***	0.090 (0.002)***	-0.080 (0.026)***	-0.094 (0.031)***
15	-0.009 (0.003)***	0.090 (0.002)***	-0.068 (0.026)***	-0.079 (0.030)***
16	-0.011 (0.003)***	0.089 (0.002)***	-0.085 (0.024)***	-0.099 (0.028)***
17	-0.009 (0.003)***	0.090 (0.002)***	-0.074 (0.026)***	-0.087 (0.031)***
18	-0.014 (0.003)***	0.088 (0.002)***	-0.112 (0.028)***	-0.131 (0.032)***
19	-0.023 (0.003)***	0.085 (0.002)***	-0.188 (0.027)***	-0.220 (0.032)***
20	-0.027 (0.003)***	0.082 (0.002)***	-0.230 (0.028)***	-0.270 (0.032)***
Fit statistics				
Baseline	0.854	0.704		
F-statistic	1996.422	6886.066		
No. individuals	160,971	160,971	160,971	160,971
Observations	5,312,076	5,312,076	5,312,076	5,312,076

Note: This table presents the results for the reduced-form (RF), first-stage (FS) and second-stage (SS) effects which I estimate using Equations (5-1) and (5-2) in bootstrap samples with replacement. I present in parentheses the standard errors derived from the standard deviation of 100 bootstrap replications. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

6
Welfare Implications

In this section, I leverage the estimated sufficient statistics to analyze the fiscal and welfare effect of the 2015 Reform, which increased financial incentives to delay early retirement claiming. I employ the MVPF approach discussed in Section 2 and summarized in Equation (2-7), $MVPF = \frac{1+\gamma\Delta C}{1+BC/MC}$, where the numerator is a measure of the willingness-to-pay for the reform and captures the insurance and redistributive values of transferring an additional dollar to the targeted population g (under the assumption of homogeneous welfare weights in the population). Meanwhile, the denominator accounts for the fiscal externality or the ratio of behavioral to mechanical costs, which represents the efficiency loss (or gain) caused by behavioral responses to the pension reform.

In addition to the estimated distributions of elasticities $\{\hat{\varepsilon}_{CH}^{t-\bar{t}}\}_t$ and $\{\hat{\eta}_S^{t-\kappa}\}_t$, I also rely on a result from Ye (2022)[1] to obtain an estimate for the income elasticity of pension claiming with respect to benefits equal to $\hat{\eta}_D = 0.047$. As explained in Section 2, this elasticity governs the probability of claiming the pension after an increase in the benefit size a worker is eligible to claim.

Importantly, the predictions of claiming and retirement responses to the pension reform in Section 2 are based on a reform that introduces a notch in the pension schedule to incentivize claiming deferral (see Figure 2.1). In contrast, the 2015 Brazilian reform not only introduced such a notch but also altered incentives beyond the threshold, as the pension schedule became flat after the 85/95 discontinuity (see Figure 3.2). As a result, the claiming response after the threshold is a combination of income and substitution effects. In the implementation of the MVPF, I adopt a simplifying assumption and consider only the income effect for two reasons. First, I have not estimated a reduced-form elasticity that captures the substitution effect induced by a flat pension schedule, and, to the best of my knowledge, the literature has yet to provide an estimate for this parameter. Second, most workers prior to the reform claimed

[1] This paper explores a German reform that increased pensions for women based on their prior earnings, where it leverages the kinked relationship between prior earnings and pension subsidy size to estimate the effect on pension claiming. This variation essentially identifies an income effect, as the slope of the lifetime budget of these workers is mostly unchanged.

their pensions before reaching the 85/95 threshold, as shown in Figure 3.3, suggesting that this substitution effect would likely have a minimal impact on the results.

6.1 Implementation

Appendix G details the procedure used to create the estimated and counterfactual distributions of employment and claiming for each individual i, based on the relevant sufficient statistics. I consider the 156,196 individuals from the main sample who claimed their pensions after June 17th 2015 and had 85/95 points at claiming, such that their pensions were increased due to the 85/95 rule. I denote the estimated and counterfactual employment distributions for each quarter-year q by $\{empl_{iq}\}_q$ and $\{empl^c_{iq}\}_q$, respectively, while the distributions of claiming are $\{claimed_{iq}\}_q$ and $\{claimed^c_{iq}\}_q$. Additionally, the benefit size claimed by worker i after the reform is depicted by b_i, and b^c_i is the counterfactual absent the reform. Next, I outline the implementation of the efficiency cost $1 + BC/MC$ and the willingness-to-pay $1 + \gamma\Delta C$ for this reform.

6.1.1 Net cost

The total fiscal effect of the pension reform is defined as the difference between the net-of-benefits tax revenue collected after the reform and the net-of-benefits tax revenue that would have been collected in the counterfactual scenario. I consider three sources of tax collection: income taxes, where social security benefits are also subject to taxation, individual social security contributions by formally employed individuals, and payroll taxes paid by their employers[2]. The total cost TC is simply the negative of the fiscal impact:

$$TC = -\sum_q \frac{1}{(1+r)^{q-\bar{q}}} \sum_i \Big\{ \Big[empl_{iq} \times w_{iq}\tau - claimed_{iq} \times b_i(1-\tau)\Big] - \Big[empl^c_{iq} \times w_{iq}\tau - claimed^c_{iq} \times b^c_i(1-\tau)\Big] \Big\} \tag{6-1}$$

where r is the real interest rate, which I consider to be 3% per year (Londoño-Vélez et al., 2025), and real values are computed at $\bar{q}$, set as the last quarter of 2019. Meanwhile, the mechanical cost is calculated as the change in net-of-tax

[2]Any additional fiscal externalities can be included in this calculation provided an estimate for them. For example, if the reform increased consumption tax revenue, then this positive fiscal externality should be subtracted from the total cost of the reform.

benefit payments holding individual behavior constant:

$$MC = \sum_q \frac{1}{(1+r)^{q-\bar{q}}} \sum_i claimed_{iq}^c \times \Big[b_i - b_i^c\Big](1-\tau) \tag{6-2}$$

I calculate the total and the mechanical costs and derive the behavioral cost as $BC = TC - MC$.

6.1.2 Wilingness-to-Pay

I estimate the WTP of the 2015 Reform using the consumption-based framework derived in Kolsrud et al. (2024). The two relevant parameters to implement this approach are the risk-aversion parameter γ and the percentage difference in consumption levels between workers who are affected by the 2015 Reform and the overall population, $\Delta C = (\mathbb{E}[C_{pop}] - \mathbb{E}[C_{85/95}])/\mathbb{E}[C_{pop}]$.

In the implementation of $WTP_g^{\$1} = 1 + \gamma\Delta C$, I consider alternative calibrations for γ, while I rely in the data from ELSI-Brazil for ΔC[3]. Importantly, this survey allows me to observe whether an individual claimed an early retirement pension, her age at the time of claiming, and her household consumption in the previous month. However, there are two limitations. First, the survey is only representative of the Brazilian population aged 50 or older, which limits the measurement of consumption levels of the general population below this age threshold. Second, I do not observe the worker's years of contribution at the moment of claiming, which is necessary to determine eligibility for the 85/95 rule. I overcome this issue by estimating the years of contribution based on observable characteristics[4]. Additionally, I consider an alternative approach where I simply impute 30 and 35 years of contribution for women and men, respectively, as most workers claim as soon as they are eligible. Using the calibrated weights from the survey, I calculate the weighted average of household consumption (H.H.) and per capita household consumption (P.C.) for individuals who qualified for the 85/95 pension increase. I compute these averages for both early retirees who reached 85/95 points and claimed the pension in any given year, and for those who qualified and claimed the pension after 2015.

[3]As discussed in Section 3, this survey asks respondents about their consumption of various goods and services, including supermarket purchases, dining out, electricity, gas, and water bills, condominium fees, transportation and bus fares, phone and internet bills, leisure activities, education, health insurance plans, and other expenses.

[4]More specifically, I use the full sample from SUIBE-RAIS and estimate a fixed-effects regression that controls for gender, administrative region, educational attainment, birth year, and age at claiming to predict years of contribution. The model performs decently, with an R-squared equal to 0.420. I then apply the estimated fixed-effects to the survey to predict the years of contribution for each early retirement claimant.

6.2 Results

Figure 6.1 illustrates the efficiency cost of the reform by plotting the estimates for the total cost TC_q and the mechanical cost MC_q at each quarter, using a 3% annual real interest rate. As suggested by Equation (2-5), the behavioral effect varies depending on the distance relative to the reform. In the short-run, the reform has a positive effect as workers defer claiming and retirement until they are eligible to the 85/95 pension increase. However, this effect becomes negative in the medium-term, when the higher pensions impact the government budget through earlier labor market exit. Consequently, the overall sign of the behavioral cost is ambiguous in theory.

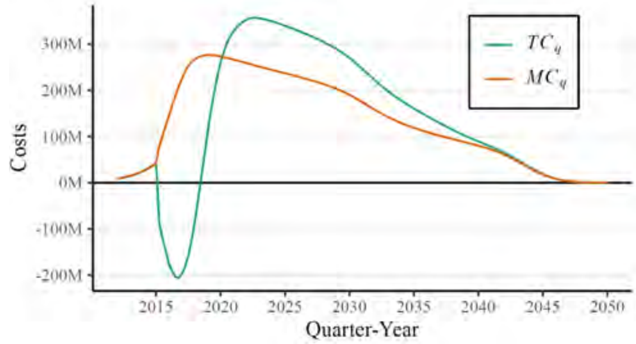
I estimate a total cost of R$129,302.91 per capita (20.19 billions on aggregate), and a mechanical cost of R$129,627.42 per capita in 2019 real terms. Overall, the estimated fiscal externality is equal to $BC/MC = -0.0025$: for each R$1.00 of pension increase, there is a small *gain* of R$0.0025 in government revenue due to behavioral adjustments. These results suggest that increasing financial incentives of deferral can be efficient, especially when compared to other pension policies. Ye (2022) finds a fiscal externality equal to 0.25 for a German reform which increased benefits of older women, while Haller (2022) estimates $1 + BC/MC$ to be equal to 0.5-0.7 and of 1.4-1.7

Table 6.1: Welfare effect of the 2015 Reform: Willingness-to-pay and MVPF

		Estimated Years of Contribution				Imputed Years of Contribution			
Claiming year		All		$\geq$ 2015		All		$\geq$ 2015	
Consumption		P.C.	H.H.	P.C.	H.H.	P.C.	H.H.	P.C.	H.H.
ΔC		-0.307	-0.215	-0.315	-0.249	-0.294	-0.198	-0.289	-0.221
No. Individuals		961	961	387	387	912	912	382	382
$WTP_g^{\$1}$	$\gamma = 1$	0.693	0.785	0.685	0.751	0.706	0.802	0.711	0.779
	$\gamma = 2$	0.387	0.570	0.370	0.502	0.412	0.603	0.422	0.558
	$\gamma = 3$	0.080	0.355	0.055	0.253	0.118	0.405	0.133	0.337
	$\gamma = 4$	-0.226	0.140	-0.260	0.004	-0.176	0.207	-0.156	0.116
$MVPF$	$\gamma = 1$	0.695	0.787	0.687	0.753	0.708	0.804	0.713	0.781
	$\gamma = 2$	0.388	0.572	0.371	0.503	0.413	0.605	0.423	0.560
	$\gamma = 3$	0.080	0.356	0.055	0.253	0.119	0.406	0.133	0.338
	$\gamma = 4$	-0.227	0.141	-0.260	0.004	-0.176	0.207	-0.156	0.117

Note: This table presents the willingness-to-pay and corresponding MVPFs for alternative implementations of the percentage difference in consumption level ΔC and the risk-aversion parameter γ. I calculate ΔC either by estimating the years of contribution based on key observables (Estimated Years of Contribution) or by imputing 30 and 35 years of contribution (Imputed Years of Contribution). Additionally, I consider either all individuals who claimed early retirement pensions in ELSI-Brazil (All) with 80/95 points or only those who claimed after 2015 ($\geq$ 2015) and qualified for the pension increase. Finally, I consider both the household consumption (H.H.) or the per capita consumption (P.C.) in the calculation of ΔC, where P.C. is the household consumption divided by the number of residents in each household.

Figure 6.1: Total and Mechanical costs of the 2015 Reform for each quarter



Note: This figure presents the total and mechanical costs of the 2015 Reform in real terms of 2019 Q4 for each quarter-year using a 3% annual real interest rate. Values are scaled in terms of millions of BRL (2019). I use the procedure detailed in Appendix G to create the counterfactual distributions of employment and claiming using the estimated sufficient statistics.

for Austrian reforms which increased the Early Retirement Age and reduced pension generosity, respectively.

Table 6.1 reports the estimated WTP for each R$1.00 transferred due to the 2015 Reform. Early retirees who benefited from the 85/95 rule consume from 19.8% to 31.5% more than the broader population. This finding is consistent with the fact that early retirees in Brazil are better off than the average worker, as achieving 30 and 35 years of contribution before the statutory retirement ages is challenging in a country with a large informal sector. Therefore, the estimated willingness-to-pay for each R$1.00 transferred to these workers is below 1 for various calibrations of the risk-aversion parameter.

Finally, I estimate an MVPF ranging from 0.69 to 0.8, 0.37 to 0.61, and 0.056 to 0.41 when γ is set to 1, 2 and 3, respectively, with a value of 0.5 in my preferred specification. In fact, as $BC/MC \approx 0$ and $\Delta C < 0$, no positive risk-aversion parameter would imply an MVPF of 1 or higher, which would indicate that individuals value this policy more than its resource costs. Hence, my findings suggest that while the 2015 Reform was efficient, given that behavioral costs are approximately zero, it would not have improved welfare if the government had financed it through a lump-sum tax on the population. This is because this policy provided insurance through higher pensions to a population that was already doing relatively well. As a result, this lump-sum tax would have redistributed resources from lower- to higher-income individuals without generating significant efficiency gains. This estimate is in line with previous work on related pension policies. Ferrari et al. (2023) and Kaufmann et al. (2024) explored reforms which incentivized workers to delay their retirement age and estimate MVPFs equal to 0.5 and 0.6, respectively. Similarly, Artmann et al. (2023) and Giesecke and Jäger (2021) found an

MVPF equal to 0.8 for pension polices which increased the benefit size of public pensions.

7
Information and Lack of Responsiveness to Incentives

In this section, I explore informational mechanisms behind the limited responsiveness to the 2015 pension reform. The average substitution elasticity of pension claiming with respect to financial incentives of -0.132 one year before the threshold is small but consistent with the existing literature (Brown, 2013; Manoli and Weber, 2016; Duggan et al., 2023; Glenzer et al., 2024). In addition, when the share of constrained individuals is not taken into account, this average elasticity is as small as -0.081. This finding suggests that there could be important optimization frictions preventing workers from properly reacting to the financial incentives from the benefit schedule and adapting accordingly to the novel set of rules created by the 2015 Reform.

In fact, the model of individual behavior from Section 2 helps to illustrate the issue of optimization frictions. In the model, financial incentives are captured by the option value from deferring the claim of social security pensions, $OV_t^K \equiv \mathbb{E}_t\{\max(V_{t+1}^W, V_{t+1}^K) - \max(V_{t+1}^R, V_{t+1}^K)$. If individuals make systematic mistakes in the calculation of OV_t^K then the model predictions would no longer hold. Such systematic mistakes could arise from a lack of knowledge about the marginal incentives produced by the reform or behavioral biases, such as present-bias. Thus, the model highlights that information is central to the success of a pension reform intended to incentivize the postponement of early retirement claiming.

In recent work, Kostøl and Myhre (2021) establish the crucial role played by information about the tax and benefit schedule in the responsiveness to financial incentives designed to encourage work among DI recipients. The authors leverage notches in the Norwegian DI system and quasi experimental variation in information recipiency about the location and slope of a new kink in the pension schedule to quantify how much information about financial incentives matters for the overall responsiveness to a change in the schedule. They find that the lack of understanding about the benefit schedule is responsible for at least 30 percent of all optimization frictions in the reaction to such incentives, as the information policy was able to increase the earnings elasticity from 0.06 to 0.15.

While the significance of information provision for the decline of optimization frictions has been settled, much less is known about the heterogeneous impacts of policies which introduce changes to the benefit schedule between households which are ex-ante more and less informed. Moreover, if these impacts are important, could the government contain such disparities with policy? In the context of a wide range of social policies such as income supplementation and subsidized health insurance, Castell et al. (2025) have recently shown that transaction costs are a relevant obstacle to benefit uptake by French job seekers. Whether this is also the case for old-age pension subsidies is still an open question.

In the following, I explore these questions in the context of the 2015 pension reform and compare the heterogeneous response to the sharp financial incentives introduced by this policy between municipalities with more and less ex-ante local knowledge. Oral et al. (2024) show that pension reforms have social multipliers whereby neighbors, coworkers and family members might enhance an individual's response to a change in the set of social security rules. Thus, residents of municipalities which were more knowledgeable before 2015 might have reacted more to the novel financial incentives brought about by the 85/95 rule. Furthermore, I examine whether the government could have enhanced the response to financial incentives by increasing the accessibility to social security field offices, where workers had to claim their pensions in person until May 2017.

7.1 Local Knowledge about Social Security Rules

Does local knowledge about social security affect the responsiveness to financial incentives introduced by pension reforms? Prior research has found that local knowledge is an important driver of responsiveness to incentives from transfer policies (Chetty et al., 2013), and that information is relevant to optimize social security decisions (Liebman and Luttmer, 2015). However, the link between local knowledge and responsiveness to financial incentives in the context of pension reforms is not well established due to the difficulty in assessing both a pension reform with sharp incentives and identifying cities with more ex-ante local knowledge. I exploit the variation induced by the 2015 pension reform and a proxy for local knowledge on claiming incentives to evaluate this link with a dynamic difference-in-differences approach that compares cities with different degrees of knowledge.

7.1.1
Framework

I develop a proxy for local knowledge about claiming incentives using the share of individuals who postpone claiming until their birthday in a given year. As discussed in Section 3, the benefit discount factor (*fator previdenciário*) used to calculate the benefit size is a function of age, years of contribution, and survival expectancy[1]. In particular, the benefit discount factor is given by:

$$f = \frac{0.31 \times \text{Years of Contribution}}{\text{Survival Expectancy}}\left[1 + \frac{\text{Age} + 0.31 \times \text{Years of Contribution}}{100}\right] \tag{7-1}$$

where Age and Years of Contribution are continuous variables where months and days are considered, but Survival Expectancy is a step function of the worker's discrete age at a given day, calculated annually by the Brazilian Institute of Geography and Statistics (IBGE). Hence, the benefit discount factor implicitly incentivizes workers to postpone pension claiming until their birthday in a given year, as the replacement rate will increase discontinuously by approximately 2 percentage points.

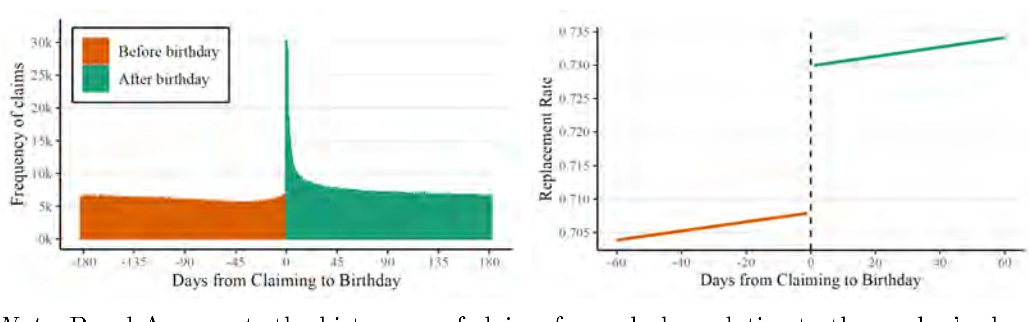
Figure 7.1 Panel B plots the discontinuity in the benefit schedule at the birthday of a worker, while Panel A plots the number of claims by distance to birthday for workers claiming pensions before the 2015 Reform. As expected, there is bunching at the birthday, which is motivated by the sudden jump in the benefit size. Still, comprehension of such deferral incentives is costly, as it requires some ability to process financial information and arithmetic concepts (Lusardi and Mitchell, 2014). Therefore, I proxy for local knowledge prior the

[1]The survival expectancy is the number of years a worker of a given age is expected to live.

Figure 7.1: Bunching of pension claiming after the birthday is driven by financial incentives

A. Histogram of claims around birthday

B. Stylized pension schedule



Note: Panel A presents the histogram of claims for each day relative to the worker's closest birthday. Panel B depicts a stylized pension schedule for each day relative to the individual's birthday, which I create using the official parameters and the survival expectancy tables from IBGE.

Table 7.1: Summary statistics – Claimants from municipalities with more and less local knowledge

	Less (Q1)	More (Q4)	Diff.		Less (Q1)	More (Q4)	Diff.
A. *Individual variables*				**B. *Regional variables***			
Male	0.753	0.652	-0.101***	Central-west region	0.031	0.003	-0.029***
White	0.694	0.838	0.144***	Northeast region	0.131	0.111	-0.020***
Birth year	1960.616	1961.516	0.901***	North region	0.027	0.001	-0.026***
< Primary education	0.334	0.215	-0.119***	Southeast region	0.470	0.483	0.012***
Primary education	0.235	0.206	-0.030***	South region	0.340	0.403	0.062***
Secondary education	0.333	0.374	0.040***	State capital	0.009	0.226	0.216***
College education	0.097	0.206	0.108***	Population size	187,597	473,157	285,560***
Age at eligibility	52.214	51.387	-0.826***	**C. *Outcomes***			
Age at claiming	54.602	53.825	-0.777***	Elig. to 85/95 (Basel.)	0.237	0.210	-0.027***
Years of contribution	35.623	35.137	-0.486***	Benefit size (Basel.)	2115.572	2359.398	243.826***
Claiming year	2015.226	2015.344	0.118***	Voluntary Elig. to 85/95	0.264	0.269	0.006***
Observations	65,800	195,676					

Note: This table presents summary statistics of pension claimants in the main sample of SUIBE-RAIS from municipalities with less (Q1) and more (Q4) local knowledge about social security incentives. I proxy for local knowledge before 2015 using the amount of bunching of pension claiming after the birthday, for municipalities with at least 30 claims prior to the reform. Columns "Diff." reports the difference in means, where $*$ indicates $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

2015 Reform with the share of workers in each municipality who claim after their birthday, conditional on claiming in a four months window around this date. To this end, I focus on the 1,955 municipalities which had at least 30 claims of early retirement before 2015.

7.1.2 Empirical strategy

I estimate the differential impact of the 2015 pension reform for municipalities with more ex-ante local knowledge using a dynamic difference-in-differences design. The treatment group consists of residents from cities in the fourth quartile of the ex-ante knowledge proxy (Q4) in the main sample, while the control are those from municipalities in the first quartile of this proxy (Q1). Table 7.1 presents the summary statistics for these workers, while Appendix Figure A9 plots the map with the location of these municipalities. There is no systematic difference in the location of cities from both groups, where some in the first quartile are even neighbors of those in the fourth quartile. Nonetheless, individuals from Q1 are considerably less educated than their Q4 counterparts.

I employ the following specification to estimate the differential impact of the reform by prior local knowledge at the individual level:

$$y_{ims} = \alpha_m + \theta_s + X_i'\gamma + \sum_{k \neq 2014\text{-S2}} \beta_k D^k_{ms} + \epsilon_{ims} \tag{7-2}$$

where m represents the municipality of individual i, s is semester when i claimed her pension, $D^k_{ms} = \mathbb{1}(m \in Q4) \times \mathbb{1}(s - 2014\text{-S2} = k)$ indicates if m is in the fourth quartile and if s is exactly k semesters after 2014-S2, α_m are municipality fixed-effects, θ_s are semester fixed-effects, and X_i are controls at the worker level. I control in X_i for educational attainment and year of birth. The main outcomes considered are the benefit size and a dummy indicating if i was eligible to the 85/95 pension increase.

The identifying assumption to find the average treatment effect of higher ex-ante local knowledge is a parallel trends assumption, such that the outcomes of interest would not have been systematically correlated with the local knowledge proxy had the reform not occurred. Although it is an untestable assumption, I check for differences in pre-reform trends between the treatment and control groups in Appendix Figure A10. I do not observe any systematic differences, even for the log of GDP per capita. Nonetheless, a possible threat to identification would arise if the measure for local knowledge about social security rules is correlated with unobservable shocks to the schooling and age composition of these municipalities. To address this concern, I add education-level and year of birth controls in X_i as fixed-effects in the regression. To the extent that these variables successfully control for the education and age composition of municipalities, this possibility should not be a concern.

7.1.3 Results

Table 7.1 and Figure 7.2 present the results. More local knowledge is associated with a significant increase of 3.1 p.p. in the probability of being eligible to the 85/95 rule in mid-2015, leading to a 39.21% increase in this probability by mid-2017, relative to the baseline. Meanwhile, the benefit size increases by R$142.40 or 6.2% of the baseline in mid-2015, and by R$139.5 or 6.07% in mid-2017.

Appendix Table A6 and Appendix Figure A11 showcase the results for additional outcomes: the log of benefit size, a dummy equal to one if the worker

Table 7.2: Effect of more local knowledge on response to the 2015 Reform – DID Results

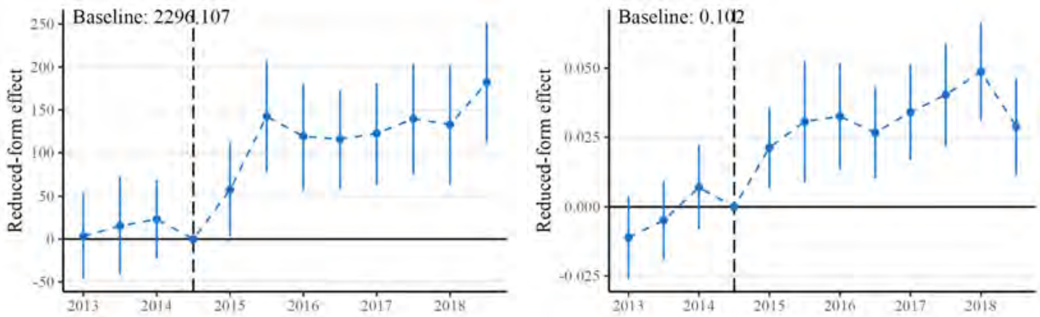
	2013 S1	2013 S2	2014 S1	2015 S1	2015 S2	2016 S1	2016 S2	2017 S1	2017 S2	2018 S1	2018 S2
Benefit size	3.39	15.3	23.2	57.5**	142.4***	119.1***	115.7***	122.6***	139.5***	132.9***	181.7***
	(25.3)	(29.2)	(23.4)	(27.6)	(32.9)	(31.4)	(29.1)	(30.1)	(32.6)	(35.2)	(35.8)
Eligibility to 85/95	-0.011	-0.005	0.007	0.021***	0.031***	0.032***	0.027***	0.034***	0.040***	0.049***	0.029***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.011)	(0.010)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)

Fit statistics	Dep. var. mean	Baseline	Baseline of Q1	Baseline of Q4	Observations
Benefit	2,468.6	2,296.1	2,115.6	2,359.4	205,893
Eligibility	0.14892	0.102	0.085	0.108	205,893

Note: This table presents the results for the dynamic difference-in-differences specification from Equation (7-2) to estimate the effect of more local knowledge on the reaction to the 2015 Reform. The baseline period is the second semester of 2014. See Appendix Table A5 for additional specifications. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Figure 7.2: Effect of more local knowledge on response to 85/95 rule - DID results

A. Benefit size **B.** Eligible to 85/95



Note: This figure depicts the results from the dynamic difference-in-differences strategy in Equation (7-2) to estimate the effect of local knowledge on reaction to financial incentives from the 2015 Reform. I present 95% confidence intervals along with point estimates for each semester, where standard errors are clustered at the municipality-level.

was eligible to the 85/95 rule voluntarily (i.e., she did not become eligible to an early retirement pension already past the 85/95 cutoff), the number of years of pension deferral and the number of claims at the municipal-level[2]. Reassuringly, the interpretation that more local knowledge positively affected the responsiveness to the novel financial incentives holds up for these outcomes. More specifically, it increased the probability of being voluntarily eligible to the 85/95 rule in mid-2015 by 3.7 p.p. or 17% relative to the baseline, while pension deferral grew by 3.15 months or 11.1% of the baseline in the same period.

In sum, these findings are consistent with residents from more informed cities adjusting more to the financial incentives introduced by the 85/95 rule. Appendix Figure A12 and Appendix Table A7 show the estimation of the substitution elasticity of claiming with respect to financial incentives from Section 4 for residents from each of the quartiles of the local knowledge proxy. While the average structural elasticity of claiming does not differ considerably among quartiles, with Q1 presenting an elasticity of -0.125 and Q4 of -0.14, the former group still has a much higher share of individuals constrained in their claiming decision: 50.6% compared to 33% in the more knowledgeable cities.

7.1.4 Robustness

I consider four alternative definitions of the knowledge quartiles to ensure robustness of the results. First, I compare municipalities from Q1 with

[2]For the municipal-level outcome, I control for population-size and GDP per capita instead of the education and year of birth fixed-effects.

municipalities from Q3, as well as Q2 with Q4. Second, I consider alternative knowledge proxies where I focus on the 2,413 municipalities which had at least 20 claims of early retirement before 2015, or the 1,435 municipalities with at least 50 claims, instead of 30 claims which I used in the main analysis. Appendix Figure E3 presents the results. Overall, the findings are robust to all exercises except for the case where I compare Q2 and Q4. Hence, my results are driven only by municipalities in the first quartile.

7.2
Accessibility to Social Security Field Offices

Could the government increase responsiveness to financial incentives through a greater coverage of social security offices? Field offices are designed to receive and analyze requests of retirement claims, as well as to inform workers about social security rules. There are several channels through which living in a location with an office could boost responsiveness to financial incentives. First, social security rules might be more salient in municipalities with a local office. Second, having an office nearby reduces travel and application costs, which have been documented as key behavior drivers towards social security (Deshpande and Li, 2019). If workers are informed about deferral incentives by agents at these offices, then the reduced application costs could increase the willingness to return after qualification for a higher pension is achieved. I combine the variation in financial incentives generated by the 2015 pension reform with a population-size discontinuity for the presence of social security offices in Brazilian municipalities to analyze whether more accessibility increased responsiveness to the reform.

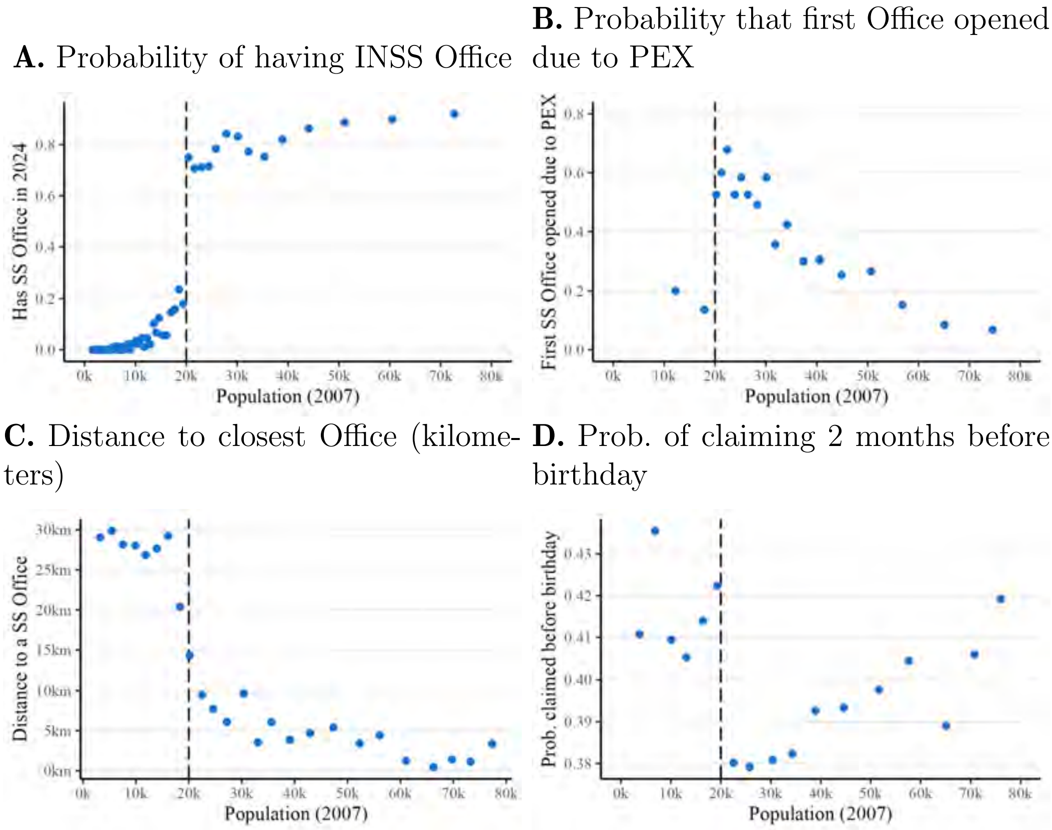
7.2.1
Framework

In 2009, the INSS decided to expand its social security field offices[3] network to all municipalities which had at least 20 thousand residents in 2007. This plan was called *Plano de Expansão da Rede de Atendimento* (PEX)[4] and

[3]INSS field offices are known as *Agências de Previdência Social* (APS).

[4]The year whose population estimate was used by INSS to decide which municipalities would be considered for a PEX field office is not publicly available, as these estimates are yearly updated by IBGE. However, there is compelling evidence that the population estimate from 2007 was considered. First, such estimates are released around the end of each calendar year, and the PEX was announced in May 2009, so the major contenders are the population estimates from 2007 and 2008. Appendix Figure A13 presents the number of PEX field offices opened for each bin of 100 residents from the 2007 population estimate. There is a clear discontinuity at the 20 thousand cutoff, whereby the population estimate from 2007 was presumably the one utilized for determining which municipalities would benefit from PEX.

Figure 7.3: Municipalities with 20 thousand residents in 2007 are more likely to have a field office



Note: This figure presents binscatter plots (Cattaneo et al., 2024) for key variables related to accessibility to INSS field offices. Panels A and B are calculated at the municipality-level and plot the probability of a city having a field office by 2024 based on its population size in 2007, as well as the probability that the first office in a municipality was opened due to PEX. Panels C and D are calculated at the individual-level and present the distance to the closest field office and the probability of claiming before the birthday, conditional on claiming in a 4-months window around this date.

was projected to create 720 new offices (INSS, 2009). Prior to 2009, only 1,110 out of 5,550 municipalities had a local office such that accessibility was fairly limited. Workers faced high travels costs and lengthy on-site waiting periods to apply for a retirement pension, as claiming was strictly in-person until May 2017[5].

Figure 7.3 Panel A depicts the binscatter plot for the probability that a municipality has a INSS field office by its population size in 2007, and Panel B presents the binscatter plot for the probability that a municipality's first field office was opened due to PEX. Consistent with the parameters of expansion from PEX, there is a clear discontinuity in both of these probabilities. Panel C displays the binscatter plot for the distance a worker in the full sample prior to May 2017 faced to get to the closest field office, and Panel D shows the

[5]In the first semester of 2017, the INSS created an online platform called *Meu INSS* which allowed individuals to claim their pensions remotely.

binscatter plot for the probability that a worker has claimed the pension in a 2-months window before her birthday. As discussed in Section 7.1, filing for an early retirement pension right before one's birthday is indicative of a lack of understanding of social security rules, such that the discontinuous drop at the 20 thousand residents cutoff is suggestive evidence that more accessibility to social security field offices positively impacts the responsiveness to financial incentives.

7.2.2 Empirical strategy

I use the population-size discontinuity at the 20 thousand residents threshold in a fuzzy RD design to explore differential impacts of more accessibility to field offices on the responsiveness to financial incentives introduced by the 2015 pension reform. The dataset consists of all early retirement claims from June 17th 2015 to April 30th 2017[6] and the outcomes are calculated at the municipality-level. I run the following first- and second-stage fuzzy RD regressions:

$$P_m = \alpha_0 + \alpha_1 1(Z_m \geq 20,000) + f(Z_m) + \varepsilon_m \tag{7-3}$$

$$y_m = \delta_0 + \delta_1 \widehat{P_m} + f(Z_m) + u_m \tag{7-4}$$

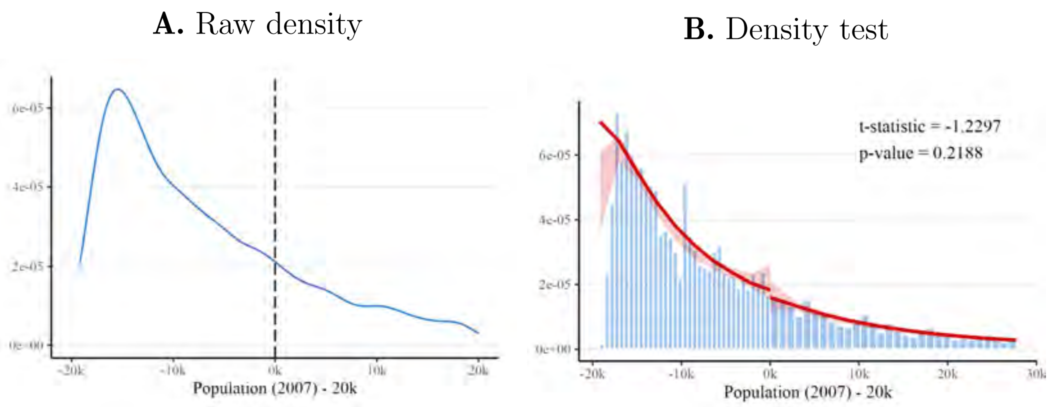
where the running variable Z_m is the population-size of municipality m in 2007, $\mathbb{1}(Z_m \geq 20,000)$ is a dummy equal to one if m had at least 20 thousand residents in 2007, P_m is a dummy equal to one if m has a social security field office, $f(\cdot)$ is a smooth function of the running variable, and y_m are the outcomes for municipality m. I consider several outcomes such as the probability of claiming at the hometown, the years of contribution, the eligibility to the 85/95 rule, the actual and actuarial replacement rates[7], and the benefit size. I calculate robust standard-errors with a triangular kernel and a linear polynomial based on Calonico et al. (2014) and employ the optimal bandwidths from Calonico et al. (2020).

The identifying assumptions to recover the local average treatment effect of the presence of social security offices are the continuity of the potential outcomes, local random assignment, and some IV-related assumptions (Lee and Lemieux, 2010). The continuity assumption should hold as there was no other policy that generated a discontinuity at the 20 thousand residents

[6] June 2015 is the month in which the pension reform took place, while May 2017 is the period in which the INSS created an online application platform that reduced the relevance of local offices in pension claiming.

[7] The former is the benefit size divided by the worker's average earnings, while the latter is the benefit size divided by the worker's average earnings up to the cap of the *teto previdenciário*.

Figure 7.4: Evidence of no-manipulation around the 20k residents cutoff



Note: This figure plots the evidence of no-manipulation aroung the threshold of 20 thousand residents. Panel A depicts the raw density at the municipality-level, while Panel B presents the density test from Cattaneo et al. (2018).

cutoff in 2007. A potential concern for this assumption would be the *Fundo de Participação de Municípios* (FPM), which uses population-size discontinuities to assign federal transfers to local governments (Brollo et al., 2013). However, the closest cutoff from the FPM is at 23,773 residents, such that the continuity assumption across the 20,000 threshold should be valid. Moreover, it is also reasonable to assume that local random assignment is valid given that the PEX program was announced in 2009 and utilized the population-size measure from 2007. Hence, municipalities could not have misreported their number of residents in order to be eligible to the field offices network expansion. To further assess validity of this assumption, I present in Figure 7.4 the density test from Cattaneo et al. (2018) to check if there is manipulation of the density function of the running variable around the cutoff. The t-statistic of this test is -1.22 such that I cannot reject the null hypothesis of continuity with a p-value equal to 0.218.

At last, the IV-related assumptions are the relevance and exogeneity of the instrument. The first one states that there should be a significant discontinuity in the probability of having a field office at the cutoff. I ensure its validity by running the first-stage regression in Figure 7.5 using a 5,000 bandwidth and in Table 7.3 using the optimal bandwidth. The first-stage is statistically significant and large as the RD estimate is 0.514. The second IV-related assumption requires that being above the cutoff should impact the outcomes only through the higher probability of having a social security office. This is very likely to hold as there is no other policy discontinuity exactly at this cutoff such that a marginally higher number of residents should not impact the relevant outcomes other than through the increased probability of having a local office. To assess validity, I check in Table 7.3 and Appendix

Table 7.3: First-stage and Differences in covariates at the cutoff for population size

Variable	Mean (Left)	Mean (Right)	RD estimate	CI 95%	Bandwidth	Observations (Left)	Observations (Right)
A. *First-stage*							
Office at hometown	0.149	0.755	0.514***	[0.377 0.651]	6027.468	596	363
B. *Balance test*							
Male	0.575	0.622	0.046	[-0.042 0.133]	7157.174	731	411
White	0.637	0.565	-0.009	[-0.113 0.095]	8452.063	876	452
Completed High school	0.495	0.486	-0.040	[-0.134 0.053]	5995.415	593	360
Completed College	0.109	0.116	-0.033	[-0.093 0.027]	7354.454	754	418
Birth year	1960.013	1960.061	0.280	[-0.614 1.173]	5937.695	585	359
Age at eligibility	53.181	53.381	-0.003	[-0.878 0.872]	7914.145	821	436
High earnings	0.326	0.378	0.009	[-0.077 0.096]	7237.402	739	415
Avg. Earnings	2795.019	3093.179	65.692	[-617.104 748.488]	6836.134	697	400
Age at claiming	55.959	55.839	-0.347	[-1.224 0.531]	6128.869	613	367
Claiming year	2015.973	2015.921	-0.074	[-0.188 0.041]	6652.848	674	394
Number of claims	18.548	28.231	-6.755	[-17.537 4.027]	6159.365	619	368

Note: This table presents the first-stage effect of the 20 thousand residents cutoff, and checks for differences in covariate balancing around this threshold. For the first-stage, I run Equation (7-3), while the balance tests run the reduced-form associated with Equations (7-3) and (7-4). All RD specifications use Calonico et al. (2014) and employ a linear polynomial and a triangular kernel, where the optimal bandwidth is calculated using Calonico et al. (2020). Means are calculated within the optimal bandwidths. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Figure A14 whether there is differential selection by running the specification with observable characteristics of municipalities as the dependent variables. Reassuringly, none of the covariates are statistically significant at this cutoff.

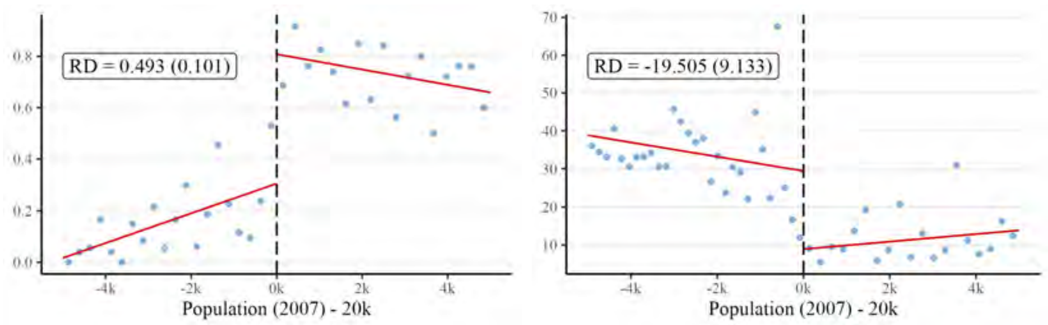
7.2.3 Results

Appendix Figure A15 depicts the reduced-form effects using a 5,000 bandwidth and Table 7.4 presents the results from the fuzzy RD strategy. As expected, I find that more accessibility to a field office increases the probability of claiming at the worker's municipality of residence by 48.9%. However, none of the other outcomes have statistically significant results. One explanation for the null effects could be that residents from some municipalities below the cutoff were not too impacted by the lack of an office, which could be the case if a neighboring city already had one. I factor in this possibility of heterogeneity in the first-stage by running the fuzzy RD specification using the distance to the closest office as the endogenous variable P_m. The results in Appendix Table A8 show that the distance to an office drops by 23.8 kilometers at the cutoff, but the second-stage results are still not statistically significant. Additionally, it could be the case that some groups are impacted by the reduction in application costs and waiting time while others are not. Appendix Table F3 presents the results for heterogeneity analyses by gender, earnings

Figure 7.5: First-stage effect: RD estimates

A. Prob. has an INSS Office

B. Distance to closest INSS Office (in kilometers)



Note: This figure depicts the RD plot for the first-stage effect of the cutoff on the probability of a municipality having a field office. For this specification, I employ a linear polynomial and a triangular kernel, and set the bandwidth to 5,000.

and educational attainment, where I calculate the outcomes at the municipal-level for each group separately. I find that women and workers with college education are among the most impacted on their probability of claiming the pension at their hometown. Nevertheless, all other pension-related outcomes are still statistically insignificant.

I interpret these results as indicative that either social security workers were not effectively informing claimants about the financial incentives of claiming deferral, or that workers with the updated information were still too impatient to return to the office conditional on already being there. Anecdotal evidence points to the existence of high travel and waiting costs related to going to a social security office such that it is plausible to believe that there are high rates of discounting. Further work is required to assess which of these two explanations better rationalizes this phenomenon.

Table 7.4: Fuzzy RD Estimates

Variable	Robust		Conventional		Bandwidth	Observations	
	RD est.	SD	RD est.	SD		(Left)	(Right)
Claimed in hometown	0.486***	0.088	0.514***	0.075	7275.171	739	414
Years of contribution	-0.046	0.654	-0.016	0.564	4949.798	461	308
Age + Years of contribution	-0.839	1.292	-0.813	1.128	4622.580	426	289
Eligible to 85/95	-0.013	0.097	-0.032	0.084	4871.683	454	304
Pension deferral (years)	-0.308	0.447	-0.423	0.391	4739.168	440	295
Actuarial Replacement rate	-0.031	0.031	0.328	0.027	4468.170	412	276
Actual replacement rate	-0.006	0.077	-0.023	0.067	4922.087	461	306
Benefit size (BRL 2019)	-71.655	306.790	-37.887	263.286	5623.131	540	341
Last year employed (until 2020)	0.376	0.368	0.415	0.322	6272.460	634	375
Number of claims	-15.929	11.876	-10.780	9.873	5714.718	552	349

Note: This table presents the second-stage coefficients of Equation (7-4) estimated using the population-size cutoff of 20 thousand residents in 2007 to instrument for the presence of an INSS field office. I run the specification with a linear polynomial and a triangular kernel, and optimal bandwidths are calculated using Calonico et al. (2020).

7.2.4 Robustness

I perform several robustness checks. First, Appendix Table E3 shows that the results are robust to changes in the kernel and polynomial order, while the significant effect for probability of claiming at hometown disappears once I consider alternative cutoffs, which is reassuring. Moreover, Appendix Table A9 and Appendix Table A10 present the results where I run at the municipal-level for claimants before the 2015 Reform and at the individual-level[8] for claimants after the reform, respectively. Likewise, the null results are robust to these alternative datasets.

[8]For the individual-level analysis, I restrict the dataset to municipalities from 0 to 40 thousand residents in 2007 and calculate the optimal bandwidths from Calonico et al. (2020).

8
Conclusion

Social security reforms have strengthened financial incentives embedded in pension schedules to encourage pension claiming deferral. The fiscal impacts of such reforms are unclear, as incentivizing deferral positively affects government revenue through pension deferrals and delayed retirement in the short-run, while higher pensions *conditional on claiming* could incentivize labor market exit. This paper evaluates the fiscal and welfare effects of a Brazilian pension reform which created unusually large financial incentives to delay early retirement claims until an individual-specific threshold was achieved. I show that the responsiveness to the 85/95 rule was limited, with an average elasticity of pension claiming equal to -0.132. In addition, I find that higher pensions lead workers to exit the labor force sooner, which corroborates a large literature on income effects of public pensions.

The welfare analysis indicates that while the reform's fiscal externality was close to zero, suggesting limited to no efficiency costs, the targeted population was already better of than the average Brazilian aged 50 or older, such that the willingness-to-pay was low. Hence, I estimate an MVPF equal to 0.3-0.6 when the risk-aversion parameter is set to 2. This indicates potential welfare losses from the 2015 Reform. Furthermore, I explore informational mechanisms behind the limited responsiveness to the 2015 Reform. I find that workers from municipalities with higher ex-ante knowledge about social security rules were more likely to respond to the reform, but that more accessibility to social security field offices was not able to improve responsiveness to the newly introduced financial incentives.

These findings have important policy implications. First, I show that pension reforms that increase deferral incentives can be efficient. However, it is unclear if this would hold if the targeted population were more liquidity constrained, which would imply a higher willingness-to-pay. Since the benchmark for a welfare-improving reform is to balance limited distortionary effects with high insurance and redistributive values, it is uncertain whether increasing deferral incentives could achieve this goal in other contexts. Second, I contribute to a growing literature on how differential access to information influences responses to financial incentives from tax and benefit schedules. I find that local knowledge is a relevant driver of this behavior, which suggests that pension reforms may exacerbate existing inequalities if not well-informed by policy-makers.

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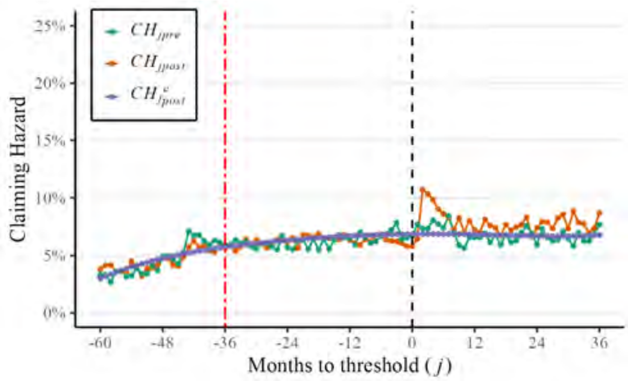
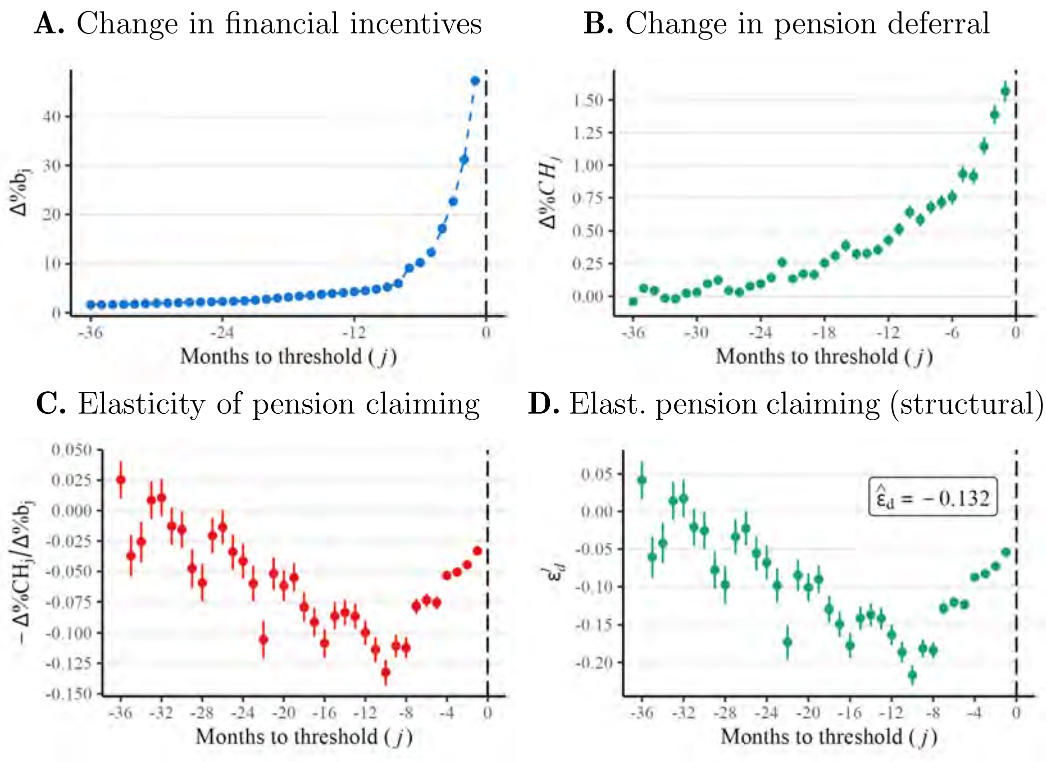
A
Additional Figures and Tables

Figure A1: Difference-in-bunching strategy: Counterfactual for Minimum-wage earners



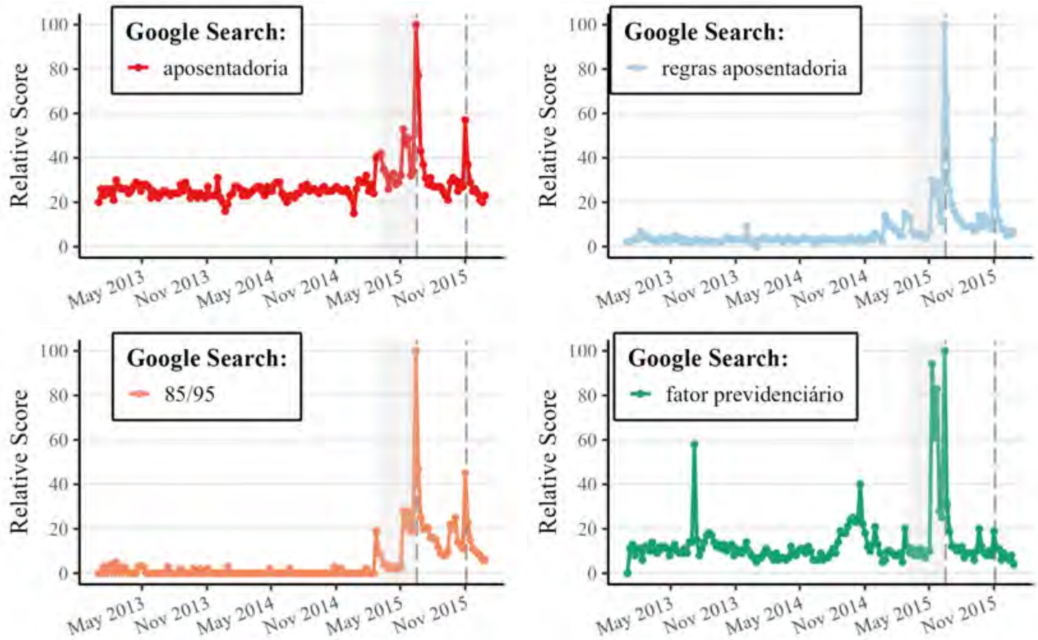
Note: This figure presents the results from the difference-in-bunching strategy applied to the minimum-wage earners sample. I create a counterfactual claiming hazard using Equation (4-4). The red dotted line represents $\pi_L = -36$, and I use a fifth order polynomial $F = 5$.

Figure A2: Change in financial incentives, change in claiming deferral and elasticities



Note: This figure presents the results for the substitution elasticity of pension claiming with respect to financial incentives. Panel A presents the calculated change in financial incentives of deferral calculated for each month before the 85/95 threshold using Equation $(4-2)$. Panel B depicts the change in pension claiming deferral calculated using Equation $(4-1)$. Panel C presents the elasticity calculated as the change in deferral divided by the change in incentives, and Panel D presents the structural elasticity defined in Equation $(4-3)$.

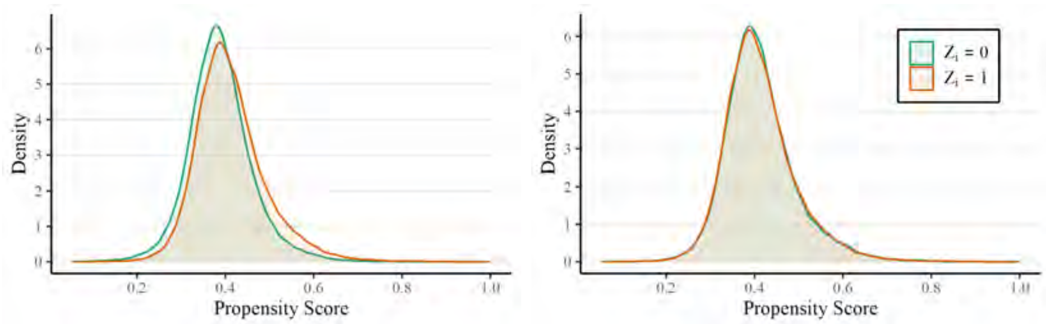
Figure A3: Evidence of no anticipation to the 2015 Reform: Google Trends



Note: The figure presents Google Trends searches of social security related terms from January 2013 to December 2015 in Brazil. I consider searches for terms of "retirement" ("aposentadoria"), "retirement rules" ("regras aposentadoria"), "benefit replacement rate" ("fator previdenciário") and "85/95". There is clear a peak in Google searches at the time of the reform in June 2015, while the rest of the period is relatively constant. The main deviation from the trend is in the search for the benefit replacement rate in June 2013 and October 2014. However, both are explained by periods of political turbulence. First, June 2013 was characterized by widespread political demonstrations in Brazil known as "Jornadas de Junho", when the end of the *fator previdenciário* was campaigned. Furthermore, October 2014 was marked by the second term of the 2014 presidential elections in Brazil, when one of the candidates promised to repeal the "fator previdenciário" if elected. As he was not elected, the searches for benefit replacement rate return to the former trend by November 2014.

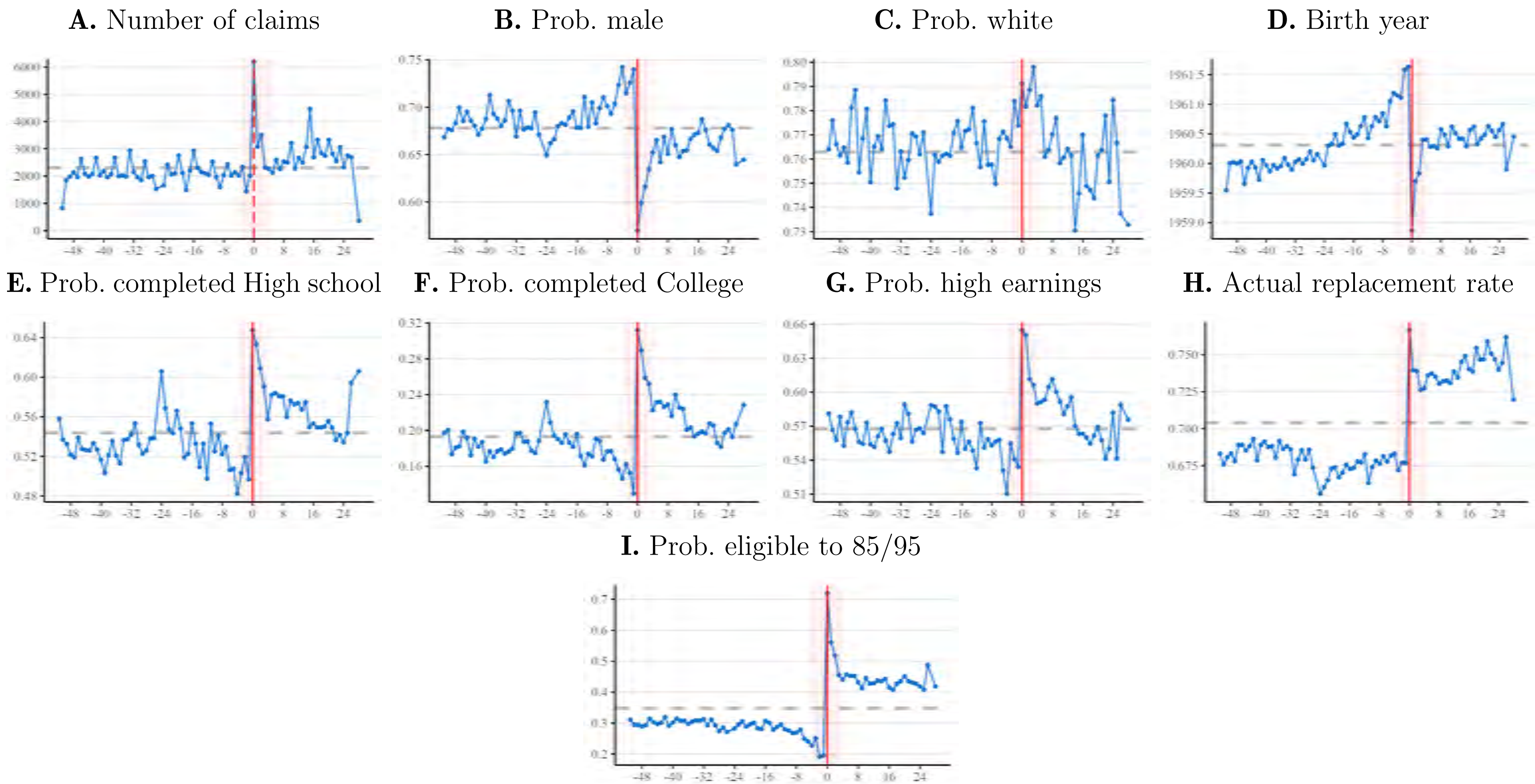
Figure A4: Propensity scores by treatment status $Z_i = 0$ and $Z_i = 1$

A. Raw density **B.** Density weighted by IPW



Note: The figure presents the density for the propensity scores for treated ($Z_i = 1$) and control ($Z_i = 1$) individuals. The sample are individuals from the main sample of SUIBE-RAIS who claimed a pension between July 2014 and December 2015, excluding those who claimed in a 2-months window around this date. Given covariates such as gender, birth year, education, most common occupation (CBO-4), most common firm sector (CNAE-3), and municipality, I estimate the probability of claiming a pension after the reform in June using a Logit model. The figure plots the estimated propensity scores of those who claimed after the reform and those who claimed before. I also plot the density using an inverse probability reweighting scheme to ensure balance between both groups.

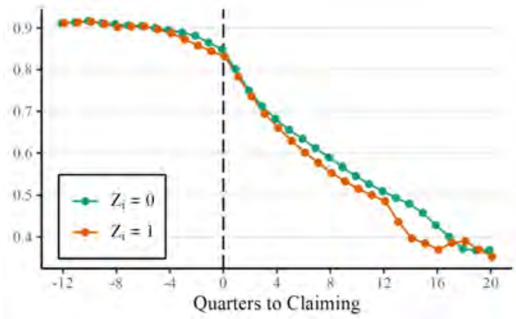
Figure A5: Descriptive statistics by claiming week around the 2015 Reform



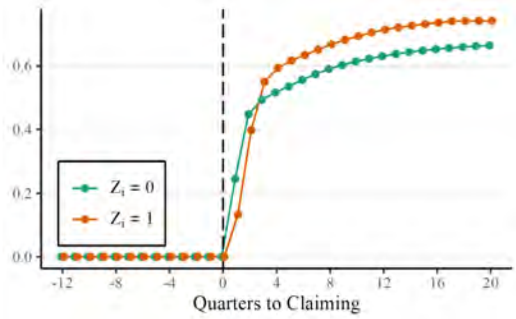
Note: This figure plots descriptive statistics of individuals in the main sample who claimed their pensions from July 2014 to December 2015. I calculate the average of key demographic and pension-related characteristics for workers who claimed in each week relative to the 2015 Reform. The red line indicates the week when the reform was enacted, and the red regions represent a 2-months window around this date. The dashed grey line illustrates the average of each variable across all weeks, excluding those who claim within the 2-months window around the reform.

Figure A6: Trends by treatment status $Z_i = 0$ and $Z_i = 1$

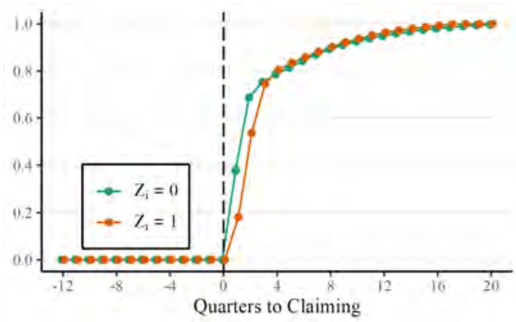
A. Prob. employment



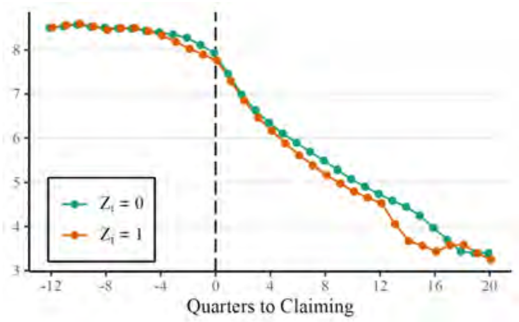
B. Actual Replacement rate



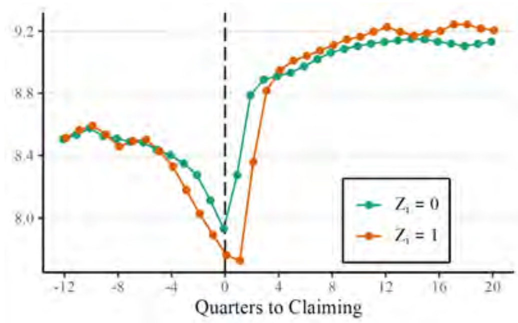
C. Prob. benefit was issued by INSS



D. Log Earnings



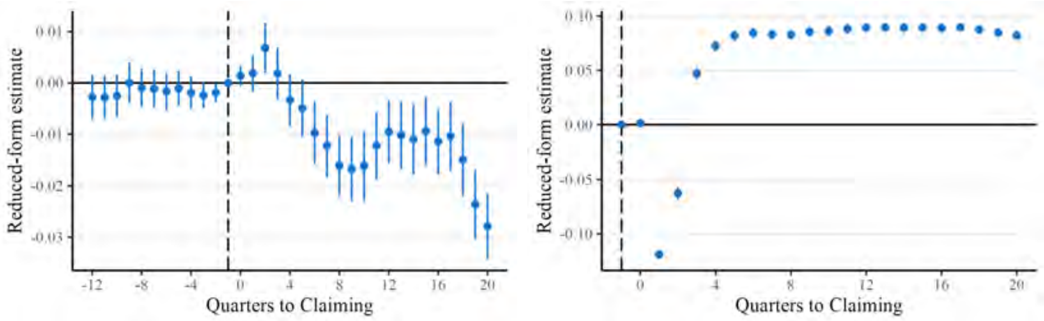
E. Log Earnings + Benefit



Note: This figure plots the trends in key outcomes for the treatment ($Z_i = 1$) and control ($Z_i = 0$) groups, for each quarter relative to the claiming period and using the inverse probability weighting scheme.

Figure A7: Reduced-form and First-stage Results using TWFE

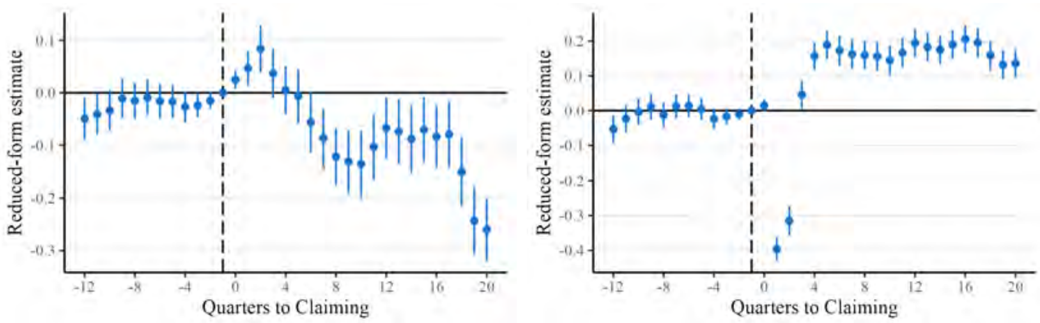
A. Probability of employment **B.** Actual Replacement rate



Note: This figure plots the dynamic coefficients with a 95% confidence interval from the two-way-fixed-effects estimator for the reduced-form (Equation (5-1)) and first-stage effects of the reform (Equation (5-2)). I employ the main sample restricted to individuals who claimed their pension between July 2014 and December 2015, excluding a 2-months window around the reform date. Standard errors are clustered at the individual-level.

Figure A8: Results: Additional outcomes

A. Log Earnings **B.** Log Earnings + Benefit

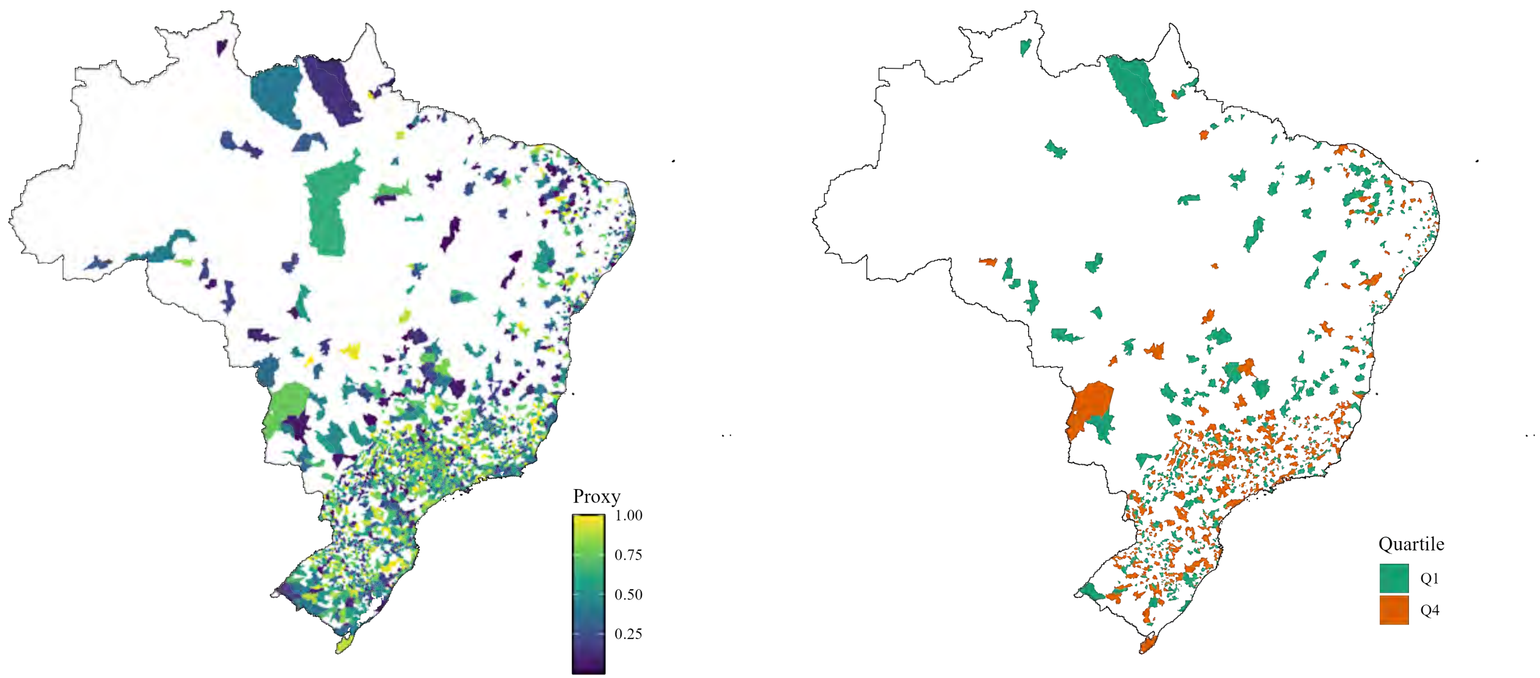


Note: This figure plots the dynamic coefficients with a 95% confidence interval from the two-way-fixed-effects estimator for the reduced-form effect (Equation (5-1)) of the reform on log earnings (unconditional on employment) and log income (or the sum of labor earnings and pension income). I employ the main sample restricted to individuals who claimed their pension between July 2014 and December 2015, excluding a 2-months window around the reform date. Standard errors are clustered at the individual-level. Standard errors are clustered at the municipality-level.

Figure A9: Local Knowledge proxy - Maps

A. Proxy value by municipality

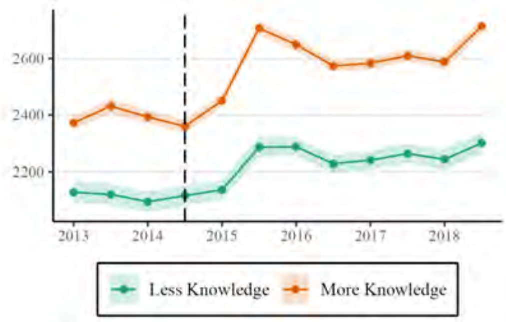
C. 1st and 4th quartiles



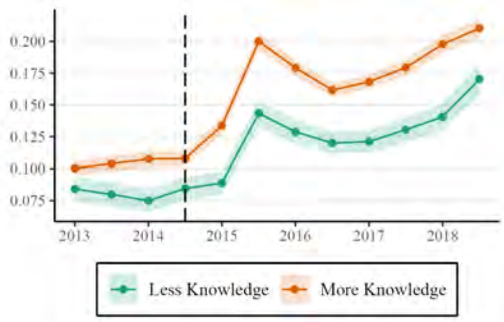
Note: This figure presents geographical descriptive evidence on the Brazilian municipalities with more and less local knowledge on social security rules. I define local knowledge in Section 7 using the share of claimants prior to 2015 who claimed their pension 2 months after their birthday, conditional on claiming in a 4 months window around this date. I consider only the municipalities which had at least 30 observed claims of social security until 2015. Panel A presents a map of the country where each municipality is colored according to the value of the proxy for local knowledge. Panel B depicts which municipalities are in the first and fourth quartiles of this proxy.

Figure A10: Trends for municipalities with more and less local knowledge

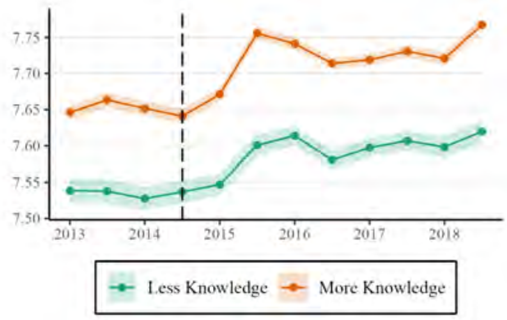
A. Benefit size



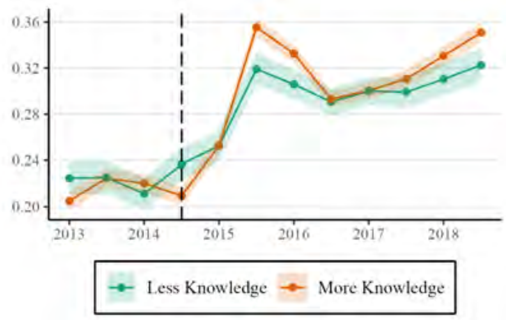
B. Eligibility to 85/95



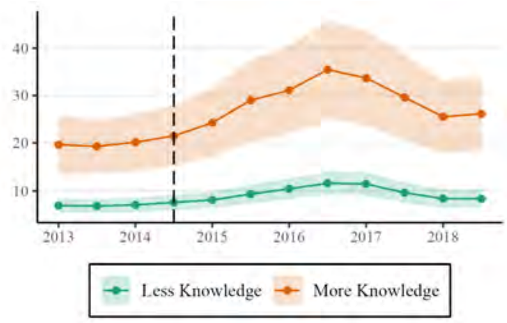
C. Log Benefit



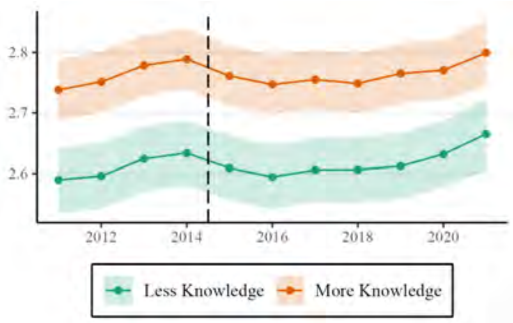
D. Voluntary Eligibility to 85/95



D. Number of claims (municipal-level)

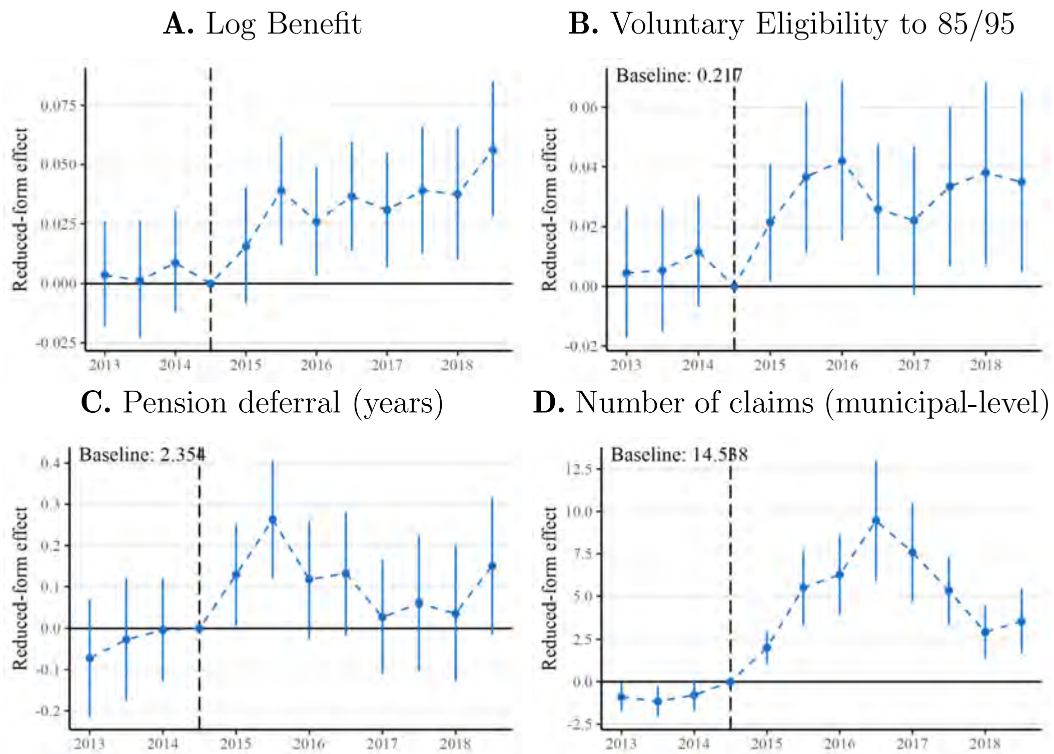


D. Log GDP per capita (municipal-level)



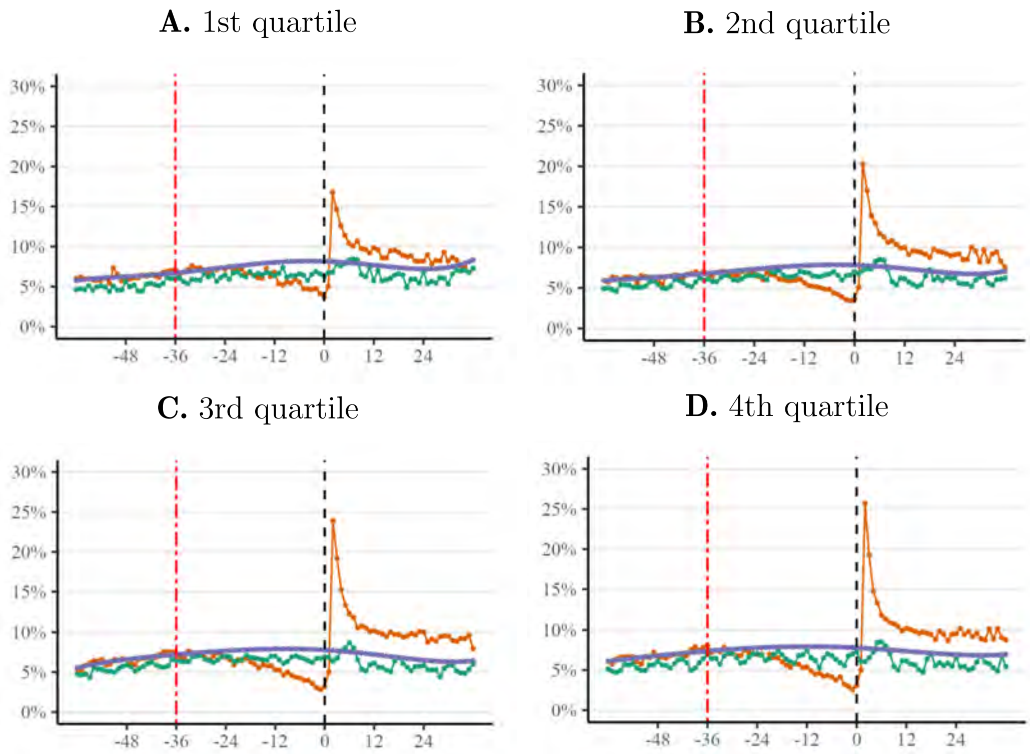
Note: This figure plots the trends in key outcomes for claimants in municipalities with more (4th quartile) and less (1st quartile) local knowledge, for each semester relative to the 2015 Reform period.

Figure A11: Effect of more local knowledge on response to 85/95 rule - Additional DID Results



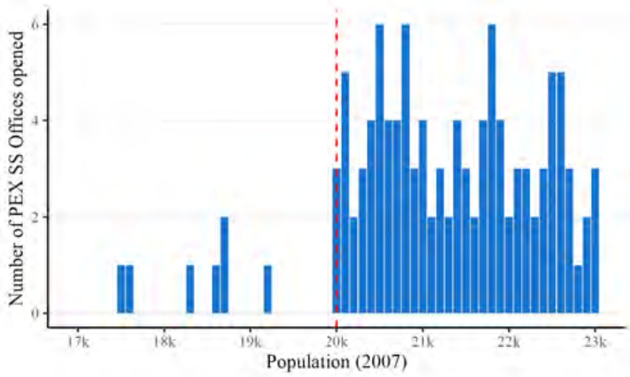
Note: This figure depicts additional results for from the dynamic difference-in-differences strategy in Equation (7-2) to estimate the effect of local knowledge on reaction to financial incentives from the 2015 Reform. I present 95% confidence intervals along with point estimates for each semester.

Figure A12: Heterogeneity: Claiming hazard by local knowledge proxy



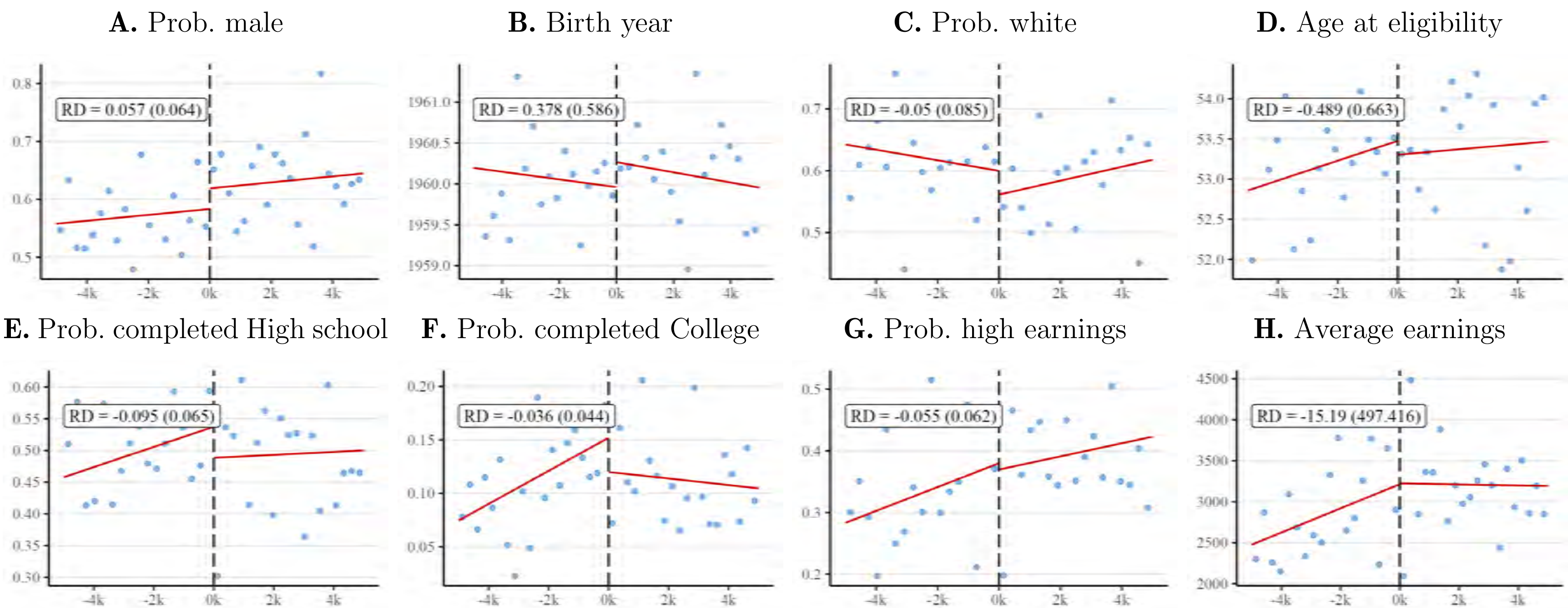
Note: This figure presents the results of the difference-in-bunching strategy depicted in Figure 4.3 to create a counterfactual claiming hazard using Equation (4-4). I create a counterfactual separately for claimants in each quartile of the local knowledge proxy. The red dotted line represents $\pi_L = -36$, and I use a fifth order polynomial $F = 5$.

Figure A13: Evidence that PEX used the population-size from 2007 (IBGE) to determine the expansion



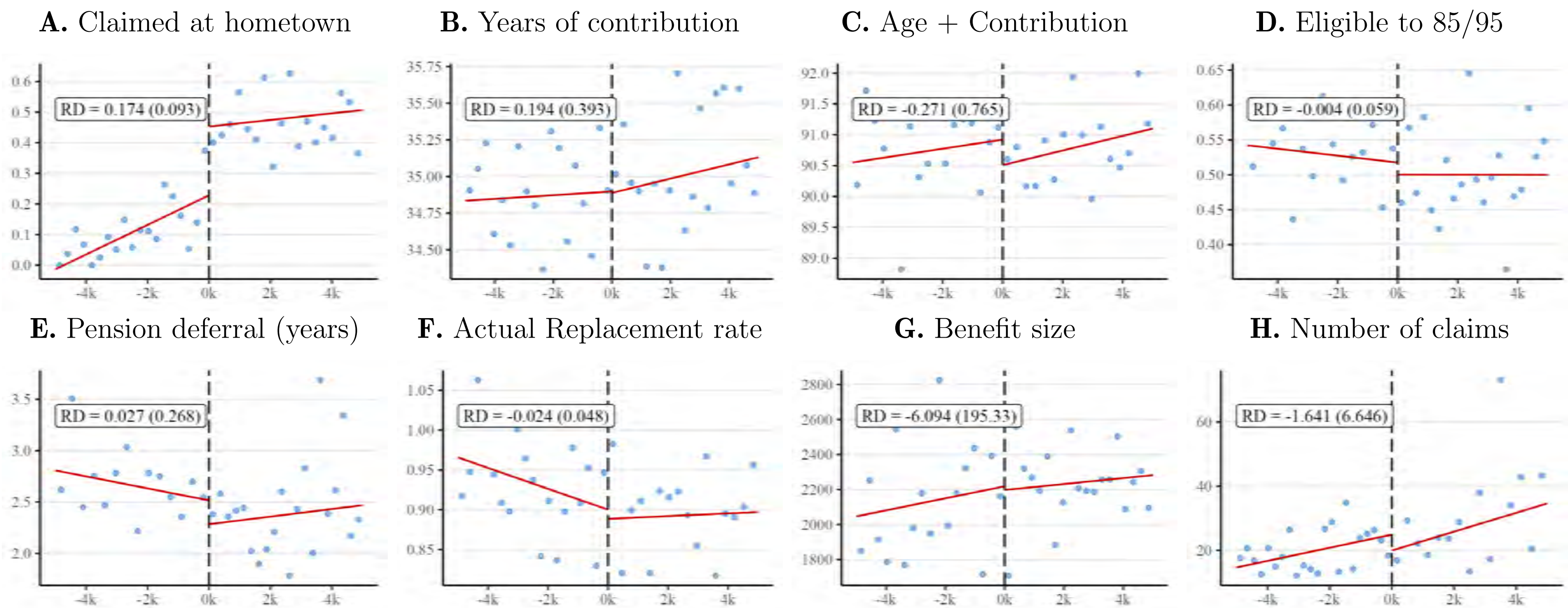
Note: This figure presents the histogram of social security field offices created as a result of the PEX program for each bin of 100 residents, based on the population-size from 2007 (IBGE). For each bin of 100 residents, I calculate the number of municipalities which had a field office opened due to PEX. The red dashed line represents the 20 thousand residents cutoff.

Figure A14: Balance test: Differences in covariates at the cutoff for population-size



Note: This figure depicts the RD plots for the reduced-form effect of the cutoff on observable characteristics of municipalities. For this specification, I employ a linear polynomial and a triangular kernel, and set the bandwidth to 5,000.

Figure A15: Reduced-form effect of the population-size discontinuity



Note: This figure depicts the RD plots for the reduced-form effect of the cutoff at 20 thousand residents in 2007 (IBGE) on pension-related outcomes at the municipality-level. For this specification, I employ a linear polynomial and a triangular kernel, and set the bandwidth to 5,000.

Table A1: Summary statistics – Expanded

	Full sample					Main sample				
	Mean	SD	Q25	Median	Q75	Mean	SD	Q25	Median	Q75
A. *SUIBE-RAIS variables*										
Male	0.633	0.482				0.665	0.472			
White	0.757	0.429				0.765	0.424			
Completed high school	0.532	0.499				0.562	0.496			
Completed College	0.183	0.386				0.204	0.403			
Birth year	1960.888	5.120	1957	1961	1964	1960.968	5.109	1958	1961	1965
Claiming year	2015.317	2.303	2014	2016	2017	2015.315	2.299	2014	2016	2017
Age at eligibility	51.973	5.114	48.446	51.888	55.518	51.939	5.057	48.438	51.814	55.417
Pension deferral (years)	2.419	2.704	0.667	1.250	3.250	2.376	2.611	0.667	1.250	3.250
Age at claiming	54.422	4.786	51.025	54.292	57.703	54.343	4.781	50.968	54.179	57.596
Average monthly salary (BRL 2019)	4456.557	5359.361	1600.587	2567.154	5021.667	4892.900	5539.085	1856.015	2891.623	5589.003
Actuarial replacement rate	0.718	0.154	0.614	0.694	0.798	0.718	0.155	0.614	0.693	0.798
Actual replacement rate	0.753	0.312	0.574	0.731	0.937	0.714	0.281	0.552	0.701	0.866
Benefit size (BRL 2019)	2385.163	1345.317	1227.269	2010.385	3239.524	2553.184	1334.499	1445.280	2234.209	3376.459
Age + Years of contribution	89.307	6.640	85.000	89.126	93.921	89.474	6.607	85.290	89.312	94.058
Years of contribution	34.892	3.520	31.321	35.525	36.710	35.137	3.462	31.925	35.619	36.863
Did not have 85/95 points	0.797	0.402				0.798	0.402			
B. *RAIS (2003-20) variables*										
Prob. employment	0.591	0.492				0.605	0.489			
Weekly hours	41.701	5.085	40	44	44	41.630	5.114	40	44	44
Monthly salary (BRL 2019)	3167.462	7139.332	0.000	1407.469	3359.358	3496.373	7520.012	0.000	1680.272	3808.930
Monthly salary (conditional)	5355.636	8629.171	1705.310	2802.034	5762.865	5775.481	8958.241	1930.248	3102.681	6254.512
Last year formally employed	2017.515	3.166	2016	2019	2020	2017.686	3.006	2016	2019	2020
Individuals			1,135,670					1,003,118		
Observations (RAIS 2003-20)			40,869,756					36,107,532		

Note: The table presents more details on the summary statistics for the full sample and the main sample derived from SUIBE-RAIS, presented in Table 3.1. Panel A consists of cross-sectional variables, while Panel B are variables calculated in panel at the semester-year level from RAIS.

Table A2: Substitution elasticity of pension claiming – Results

j	$\Delta\%b_j$	$\Delta\%CH_j$	$\Delta\%CH_j/(1-\kappa)$	ε^j_{CH}	$\tilde{\varepsilon}^j_{CH}$	j	$\Delta\%b_j$	$\Delta\%CH_j$	$\Delta\%CH_j/(1-\kappa)$	ε^j_{CH}	$\tilde{\varepsilon}^j_{CH}$
-36	1.623	-0.041 (0.013)	-0.067 (0.021)	0.025	0.042	-18	3.212	0.254 (0.020)	0.416 (0.030)	-0.079	-0.130
-35	1.649	0.061 (0.015)	0.100 (0.023)	-0.037	-0.061	-17	3.407	0.310 (0.021)	0.508 (0.030)	-0.091	-0.149
-34	1.693	0.044 (0.015)	0.071 (0.024)	-0.026	-0.042	-16	3.585	0.389 (0.022)	0.637 (0.031)	-0.108	-0.178
-33	1.747	-0.015 (0.014)	-0.024 (0.023)	0.009	0.014	-15	3.762	0.325 (0.021)	0.532 (0.030)	-0.086	-0.141
-32	1.814	-0.019 (0.014)	-0.031 (0.024)	0.011	0.017	-14	3.940	0.328 (0.021)	0.538 (0.030)	-0.083	-0.136
-31	1.886	0.024 (0.015)	0.039 (0.025)	-0.013	-0.021	-13	4.122	0.356 (0.022)	0.583 (0.030)	-0.086	-0.142
-30	1.952	0.030 (0.016)	0.050 (0.025)	-0.016	-0.025	-12	4.310	0.430 (0.023)	0.704 (0.031)	-0.100	-0.164
-29	2.012	0.096 (0.017)	0.157 (0.027)	-0.048	-0.078	-11	4.510	0.513 (0.024)	0.841 (0.032)	-0.114	-0.186
-28	2.077	0.124 (0.017)	0.202 (0.027)	-0.060	-0.098	-10	4.826	0.639 (0.026)	1.047 (0.033)	-0.132	-0.217
-27	2.133	0.044 (0.016)	0.072 (0.026)	-0.021	-0.034	-9	5.260	0.582 (0.025)	0.954 (0.032)	-0.111	-0.181
-26	2.191	0.030 (0.016)	0.049 (0.026)	-0.014	-0.022	-8	6.038	0.678 (0.027)	1.110 (0.033)	-0.112	-0.184
-25	2.246	0.076 (0.017)	0.125 (0.027)	-0.034	-0.056	-7	9.129	0.715 (0.027)	1.172 (0.033)	-0.078	-0.128
-24	2.302	0.096 (0.018)	0.157 (0.028)	-0.042	-0.068	-6	10.288	0.756 (0.028)	1.239 (0.034)	-0.074	-0.120
-23	2.359	0.142 (0.018)	0.232 (0.028)	-0.060	-0.098	-5	12.346	0.932 (0.031)	1.527 (0.035)	-0.076	-0.124
-22	2.455	0.259 (0.020)	0.425 (0.030)	-0.106	-0.173	-4	17.171	0.917 (0.031)	1.502 (0.035)	-0.053	-0.088
-21	2.585	0.134 (0.018)	0.219 (0.028)	-0.052	-0.085	-3	22.638	1.143 (0.034)	1.873 (0.037)	-0.051	-0.083
-20	2.771	0.171 (0.019)	0.280 (0.029)	-0.062	-0.101	-2	31.183	1.388 (0.038)	2.273 (0.040)	-0.044	-0.073
-19	3.006	0.166 (0.019)	0.271 (0.028)	-0.055	-0.090	-1	47.315	1.567 (0.041)	2.567 (0.041)	-0.033	-0.054

Note: This table presents the results for the estimated substitution elasticity of pension claiming with respect to financial incentives, defined in Equation (4-3) and estimated using the difference-in-bunching strategy laid out in Section 4.2. j represents the distance in months to the threshold, and I report in parenthesis the standard deviation derived from bootstrap replications.

Table A3: Reduced-form and First-stage estimates using TWFE

Dep. Var.: Model:	Is employed (1)	Replacement rate (2)	Is employed (3)	Replacement rate (4)
-12	-0.003 (0.002)		-0.003 (0.002)	
-11	-0.003 (0.002)		-0.003 (0.002)	
-10	-0.003 (0.002)		-0.003 (0.002)	
-9	4.63×10^{-5} (0.002)		-0.0004 (0.002)	
-8	-0.0009 (0.002)		-0.001 (0.002)	
-7	-0.001 (0.002)		-0.002 (0.002)	
-6	-0.002 (0.002)		-0.002 (0.002)	
-5	-0.001 (0.002)		-0.002 (0.002)	
-4	-0.002 (0.002)		-0.002 (0.002)	
-3	-0.002* (0.001)		-0.003** (0.001)	
-2	-0.002** (0.0009)		-0.003*** (0.0009)	
0	0.001 (0.001)	0.001*** (0.0004)	0.002** (0.0010)	0.002*** (0.0004)
1	0.002 (0.002)	-0.119*** (0.002)	0.005** (0.002)	-0.113*** (0.002)
2	0.007*** (0.002)	-0.063*** (0.003)	0.008*** (0.002)	-0.054*** (0.003)
3	0.002 (0.003)	0.047*** (0.003)	0.004 (0.003)	0.052*** (0.003)
4	-0.003 (0.003)	0.072*** (0.002)	-0.0005 (0.003)	0.075*** (0.002)
5	-0.005* (0.003)	0.082*** (0.002)	-0.002 (0.003)	0.082*** (0.002)
6	-0.010*** (0.003)	0.084*** (0.002)	-0.006* (0.003)	0.081*** (0.002)
7	-0.012*** (0.003)	0.083*** (0.002)	-0.008*** (0.003)	0.078*** (0.002)
8	-0.016*** (0.003)	0.083*** (0.002)	-0.011*** (0.003)	0.077*** (0.002)
9	-0.017*** (0.003)	0.086*** (0.002)	-0.011*** (0.003)	0.079*** (0.002)
10	-0.016*** (0.003)	0.086*** (0.002)	-0.011*** (0.003)	0.080*** (0.002)
11	-0.012*** (0.003)	0.088*** (0.002)	-0.006* (0.003)	0.081*** (0.002)
12	-0.010*** (0.003)	0.089*** (0.002)	-0.003 (0.003)	0.081*** (0.002)
13	-0.010*** (0.003)	0.090*** (0.002)	-0.005 (0.003)	0.081*** (0.002)
14	-0.011*** (0.003)	0.089*** (0.002)	-0.007* (0.003)	0.081*** (0.002)
15	-0.009*** (0.003)	0.089*** (0.002)	-0.005 (0.003)	0.080*** (0.002)
16	-0.011*** (0.003)	0.089*** (0.002)	-0.007** (0.003)	0.079*** (0.002)
17	-0.010*** (0.003)	0.090*** (0.002)	-0.005 (0.003)	0.080*** (0.002)
18	-0.015*** (0.004)	0.088*** (0.002)	-0.009*** (0.004)	0.078*** (0.002)
19	-0.024*** (0.003)	0.085*** (0.002)	-0.018*** (0.003)	0.075*** (0.002)
20	-0.028*** (0.003)	0.082*** (0.002)	-0.021*** (0.003)	0.072*** (0.002)
Fixed-effects				
Indiv.	✓	✓	✓	✓
Qtr. to claim	✓	✓	✓	✓
Year	✓	✓	✓	✓
IPW	✓	✓		
Fit statistics				
Observations	5,312,043	3,541,362	5,312,043	3,541,362
Dep. var. mean	0.67287	0.55660	0.67287	0.55660
Baseline	0.855	0.705	0.855	0.704
control	0.865	0.667	0.861	0.679
Treated	0.844	0.742	0.844	0.0.742

Note: This table reports the results for the reduced-form and first-stage effects which I estimate using Equations (5-1) and (5-2) and a two-way-fixed-effects estimator in the main sample restricted to claimants from July 2014 to December 2015, excluding a 2 months window around the reform date. Standard errors are clustered at the individual-level. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table A4: Additional outcomes - Reduced-form effects using TWFE

Dep. Var.:	Log Income	Log Benefit	Log Earnings	Log Income	Log Benefit	Log Earnings
Model:	(1)	(2)	(3)	(4)	(5)	(6)
-12	-0.053*** (0.020)		-0.049** (0.021)	-0.044** (0.019)		-0.047** (0.020)
-11	-0.023 (0.020)		-0.041** (0.020)	-0.019 (0.019)		-0.042** (0.020)
-10	-0.004 (0.019)		-0.034* (0.020)	-0.003 (0.019)		-0.037* (0.019)
-9	0.010 (0.019)		-0.011 (0.019)	0.011 (0.018)		-0.014 (0.019)
-8	-0.012 (0.018)		-0.015 (0.018)	-0.011 (0.018)		-0.018 (0.018)
-7	0.012 (0.017)		-0.009 (0.018)	0.012 (0.017)		-0.014 (0.017)
-6	0.013 (0.016)		-0.016 (0.017)	0.013 (0.016)		-0.022 (0.017)
-5	0.004 (0.016)		-0.017 (0.016)	0.004 (0.016)		-0.021 (0.016)
-4	-0.024 (0.015)		-0.027* (0.015)	-0.023 (0.015)		-0.030** (0.015)
-3	-0.017 (0.011)		-0.024** (0.012)	-0.022* (0.011)		-0.031*** (0.011)
-2	-0.010 (0.008)		-0.015* (0.008)	-0.017** (0.008)		-0.022*** (0.008)
0	0.015* (0.009)	0.009*** (0.003)	0.025*** (0.009)	0.025*** (0.009)	0.004 (0.003)	0.035*** (0.009)
1	-0.396*** (0.017)	-1.59*** (0.020)	0.047*** (0.017)	-0.355*** (0.017)	-1.50*** (0.019)	0.070*** (0.017)
2	-0.315*** (0.021)	-1.27*** (0.025)	0.084*** (0.023)	-0.285*** (0.021)	-1.12*** (0.024)	0.096*** (0.023)
3	0.046** (0.021)	-0.110*** (0.022)	0.037 (0.024)	0.064*** (0.021)	0.025 (0.022)	0.053** (0.024)
4	0.156*** (0.020)	0.152*** (0.020)	0.005 (0.024)	0.169*** (0.020)	0.263*** (0.020)	0.028 (0.023)
5	0.188*** (0.021)	0.247*** (0.019)	-0.007 (0.026)	0.195*** (0.021)	0.329*** (0.019)	0.020 (0.026)
6	0.172*** (0.022)	0.270*** (0.019)	-0.056* (0.029)	0.171*** (0.022)	0.322*** (0.019)	-0.026 (0.029)
7	0.163*** (0.022)	0.242*** (0.018)	-0.086*** (0.029)	0.156*** (0.021)	0.285*** (0.018)	-0.055* (0.028)
8	0.159*** (0.021)	0.225*** (0.017)	-0.122*** (0.028)	0.150*** (0.020)	0.258*** (0.016)	-0.084*** (0.027)
9	0.156*** (0.021)	0.241*** (0.016)	-0.131*** (0.030)	0.147*** (0.021)	0.271*** (0.015)	-0.087*** (0.029)
10	0.145*** (0.022)	0.240*** (0.015)	-0.136*** (0.032)	0.135*** (0.022)	0.269*** (0.015)	-0.092*** (0.032)
11	0.166*** (0.021)	0.253*** (0.014)	-0.104*** (0.031)	0.154*** (0.021)	0.276*** (0.014)	-0.054* (0.031)
12	0.139*** (0.021)	0.233*** (0.015)	-0.122*** (0.031)	0.129*** (0.021)	0.260*** (0.014)	-0.082*** (0.030)
13	0.183*** (0.021)	0.256*** (0.012)	-0.074** (0.031)	0.164*** (0.021)	0.272*** (0.012)	-0.035 (0.031)
14	0.175*** (0.022)	0.253*** (0.012)	-0.088*** (0.033)	0.153*** (0.021)	0.267*** (0.011)	-0.057* (0.032)
15	0.190*** (0.021)	0.248*** (0.011)	-0.070** (0.032)	0.166*** (0.021)	0.258*** (0.011)	-0.038 (0.031)
16	0.206*** (0.021)	0.240*** (0.010)	-0.084*** (0.030)	0.179*** (0.020)	0.245*** (0.010)	-0.055* (0.029)
17	0.195*** (0.021)	0.247*** (0.010)	-0.080** (0.032)	0.172*** (0.021)	0.252*** (0.009)	-0.037 (0.031)
18	0.159*** (0.022)	0.225*** (0.009)	-0.150*** (0.034)	0.136*** (0.021)	0.229*** (0.009)	-0.102*** (0.033)
19	0.132*** (0.021)	0.192*** (0.009)	-0.243*** (0.032)	0.106*** (0.021)	0.193*** (0.008)	-0.194*** (0.032)
20	0.136*** (0.020)	0.162*** (0.009)	-0.260*** (0.030)	0.107*** (0.020)	0.158*** (0.008)	-0.209*** (0.029)
Fixed-effects						
Indiv.	✓	✓	✓	✓	✓	✓
Qtr. to claim	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
IPW	✓	✓	✓			
Fit statistics						
Observations	5,312,043	3,541,362	5,312,043	5,312,043	3,541,362	5,312,043
Dep. var. mean	8.7334	6.1285	6.2690	8.7334	6.1285	6.2690
Baseline	8.00		8.00	7.99		7.99
Control	8.11		8.11	8.05		8.05
Treated	7.89		7.89	7.89		7.89

Note: This table reports the dynamic coefficients from the two-way-fixed-effects estimator for the reduced-form effect (Equation (5-1)) of the reform on log earnings (unconditional on employment) and log income (or the sum of labor earnings and pension income). I employ the main sample restricted to individuals who claimed their pension between July 2014 and December 2015, excluding a 2-months window around the reform date. Standard errors are clustered at the individual-level. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table A5: Additional specifications – Effect of more local knowledge on response to the 2015 Reform

Dep. Var.:	Benefit size			Eligibility to 85/95		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
2013 S1	4.94	12.8	3.39	-0.008	-0.007	-0.011
	(30.5)	(26.5)	(25.3)	(0.008)	(0.008)	(0.008)
2013 S2	53.4*	45.9	15.3	-1.85×10^{-5}	-0.002	-0.005
	(31.3)	(30.4)	(29.2)	(0.008)	(0.007)	(0.007)
2014 S1	49.9*	48.6**	23.2	0.008	0.008	0.007
	(25.9)	(24.0)	(23.4)	(0.007)	(0.008)	(0.008)
2015 S1	70.8**	68.9**	57.5**	0.020**	0.020**	0.021***
	(32.1)	(28.3)	(27.6)	(0.008)	(0.008)	(0.007)
2015 S2	166.4***	173.8***	142.4***	0.033***	0.034***	0.031***
	(39.8)	(35.2)	(32.9)	(0.012)	(0.011)	(0.011)
2016 S1	128.9***	134.6***	119.1***	0.029***	0.030***	0.032***
	(36.0)	(33.9)	(31.4)	(0.010)	(0.010)	(0.010)
2016 S2	116.2***	120.1***	115.7***	0.022**	0.022***	0.027***
	(33.9)	(30.9)	(29.1)	(0.009)	(0.008)	(0.008)
2017 S1	132.0***	128.3***	122.6***	0.028***	0.028***	0.034***
	(39.0)	(33.4)	(30.1)	(0.010)	(0.009)	(0.009)
2017 S2	135.7***	134.3***	139.5***	0.030***	0.030***	0.040***
	(46.5)	(36.0)	(32.6)	(0.010)	(0.010)	(0.009)
2018 S1	144.0***	130.6***	132.9***	0.040***	0.038***	0.049***
	(48.6)	(37.6)	(35.2)	(0.010)	(0.010)	(0.009)
2018 S2	200.6***	181.0***	181.7***	0.021**	0.020**	0.029***
	(47.4)	(38.2)	(35.8)	(0.009)	(0.009)	(0.009)
Fixed-effects						
Municipality (977)	✓	✓	✓	✓	✓	✓
Semester-Year (12)	✓	✓	✓	✓	✓	✓
Schooling (11)		✓	✓		✓	✓
Birth year (46)			✓			✓
Fit statistics						
Observations	205,893	205,893	205,893	205,893	205,893	205,893
Dep. var. mean	2,468.6	2,468.6	2,468.6	0.14892	0.14892	0.14892
Baseline	2,296.1	2,296.1	2,296.1	0.102	0.102	0.102
Control (Q1)	2,115.6	2,115.6	2,115.6	0.085	0.085	0.085
Treated (Q4)	2,359.4	2,359.4	2,359.4	0.108	0.108	0.108

Note: This table reports the additional specifications of the results for the dynamic difference-in-differences specification from Equation (7-2) to estimate the effect of more local knowledge on the reaction to the 2015 Reform. The baseline period is the second semester of 2014. Standard errors are clustered at the municipality-level. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table A6: Effect of more local knowledge on response to the 2015 Reform – Additional results

Dep. Var.:	Log Benefit size		Voluntary Eligibility		Deferral (years)		Number of claims	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2013 S1	0.005	0.004	0.007	0.005	-0.079	-0.073	-1.19***	-0.905**
	(0.013)	(0.011)	(0.013)	(0.011)	(0.073)	(0.072)	(0.406)	(0.430)
2013 S2	0.016	0.001	0.023*	0.005	0.004	-0.027	-1.45**	-1.16**
	(0.013)	(0.012)	(0.014)	(0.010)	(0.080)	(0.075)	(0.564)	(0.461)
2014 S1	0.019	0.009	0.037***	0.012	0.016	-0.004	-0.791*	-0.791*
	(0.012)	(0.011)	(0.012)	(0.009)	(0.067)	(0.064)	(0.455)	(0.455)
2015 S1	0.020	0.015	0.030**	0.021**	0.138**	0.129**	2.28***	2.01***
	(0.014)	(0.012)	(0.012)	(0.010)	(0.062)	(0.062)	(0.578)	(0.480)
2015 S2	0.048***	0.038***	0.062***	0.037***	0.296***	0.263***	5.78***	5.51***
	(0.014)	(0.011)	(0.013)	(0.013)	(0.073)	(0.073)	(1.27)	(1.11)
2016 S1	0.028**	0.026**	0.059***	0.042***	0.141*	0.117	6.79***	6.27***
	(0.013)	(0.011)	(0.015)	(0.014)	(0.073)	(0.073)	(1.50)	(1.19)
2016 S2	0.035***	0.036***	0.036***	0.026**	0.133*	0.132*	9.97***	9.46***
	(0.013)	(0.011)	(0.012)	(0.011)	(0.074)	(0.076)	(2.13)	(1.82)
2017 S1	0.032**	0.030**	0.038***	0.022*	0.034	0.027	8.35***	7.59***
	(0.015)	(0.012)	(0.013)	(0.013)	(0.069)	(0.070)	(1.95)	(1.49)
2017 S2	0.035*	0.038***	0.049***	0.033**	0.051	0.060	6.11***	5.34***
	(0.018)	(0.013)	(0.014)	(0.014)	(0.084)	(0.084)	(1.41)	(1.01)
2018 S1	0.038**	0.037***	0.062***	0.038**	0.031	0.036	3.27***	2.92***
	(0.018)	(0.014)	(0.014)	(0.016)	(0.082)	(0.084)	(0.850)	(0.796)
2018 S2	0.059***	0.055***	0.061***	0.035**	0.152*	0.150*	3.91***	3.56***
	(0.018)	(0.014)	(0.014)	(0.015)	(0.085)	(0.084)	(0.986)	(0.963)
Population size								0.003***
								(0.0008)
GDP per capita								-0.041
								(0.029)
Fixed-effects								
Municipality (977)	✓	✓	✓	✓	✓	✓	✓	✓
Semester-Year (12)	✓	✓	✓	✓	✓	✓	✓	✓
Schooling (11)		✓		✓		✓		
Birth year		✓		✓		✓		
Fit statistics								
# Birth year	–	46	–	32	–	41	–	–
Observations	205,893	205,893	182,780	182,780	204,056	204,056	11,724	11,724
Dep. var. mean	7.6760	7.6760	0.28690	0.28690	2.4375	2.4375	17.562	17.562
Baseline	7.61	7.61	0.217	0.217	2.35	2.35	14.5	14.5
Control (Q1)	7.54	7.54	0.237	0.237	2.34	2.34	7.57	7.57
Treated (Q4)	7.64	7.64	0.210	0.210	2.36	2.36	21.5	21.5

Note: This table reports the additional results for the dynamic difference-in-differences specification from Equation (7-2) to estimate the effect of more local knowledge on the reaction to the 2015 Reform. The baseline period is the second semester of 2014. Standard errors are clustered at the municipality-level. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table A7: Heterogeneity: Substitution elasticity of pension claiming by local knowledge proxy

Heterogeneity	j	-12	-10	-8	-6	-4	-2	*Summary*	*Obs.*
1st quartile	$\Delta\%b_j$	4.196	4.663	5.504	10.032	17.027	30.571	$\bar{\Delta b} = 14.228$	56,751
	$\Delta\%CH_j$	0.184	0.551	0.495	0.471	0.737	0.719	$\Delta\bar{C}H = 0.583$	
	$\bar{\varepsilon}^j_{CH}$	-0.089	-0.239	-0.182	-0.095	-0.088	-0.048	$\bar{\bar{\varepsilon}}$ = -0.125	
		0.008	0.008	0.006	0.003	0.002	0.001	$\kappa = 0.506$	
2nd quartile	$\Delta\%b_j$	4.244	4.737	5.742	10.176	17.002	30.679	$\bar{\Delta b} = 14.680$	239,232
	$\Delta\%CH_j$	0.379	0.499	0.566	0.628	0.871	1.218	$\Delta\bar{C}H = 0.750$	
	$\bar{\varepsilon}^j_{CH}$	-0.159	-0.187	-0.175	-0.110	-0.091	-0.071	$\bar{\bar{\varepsilon}}$ = -0.127	
		0.008	0.007	0.006	0.003	0.002	0.001	$\kappa = 0.438$	
3rd quartile	$\Delta\%b_j$	4.337	4.871	6.488	10.332	17.215	31.320	$\bar{\Delta b} = 15.028$	375,936
	$\Delta\%CH_j$	0.489	0.707	0.730	0.849	0.981	1.564	$\Delta\bar{C}H = 0.940$	
	$\bar{\varepsilon}^j_{CH}$	-0.177	-0.228	-0.177	-0.129	-0.090	-0.079	$\bar{\bar{\varepsilon}}$ = -0.135	
		0.007	0.007	0.005	0.003	0.002	0.001	$\kappa = 0.364$	
4th quartile	$\Delta\%b_j$	4.405	4.941	6.402	10.418	17.506	31.853	$\bar{\Delta b} = 15.295$	171,160
	$\Delta\%CH_j$	0.476	0.761	0.867	0.913	0.900	1.632	$\Delta\bar{C}H = 1.035$	
	$\bar{\varepsilon}^j_{CH}$	-0.161	-0.230	-0.202	-0.131	-0.077	-0.077	$\bar{\bar{\varepsilon}}$ = -0.140	
		0.009	0.009	0.007	0.005	0.003	0.002	$\kappa = 0.330$	

Note: This table reports the results of the difference-in-bunching strategy depicted in Figure 4.3 to create a counterfactual claiming hazard using Equation (4-4). I estimate the pension claiming elasticity separately for claimants in each quartile of the local knowledge proxy. $\bar{\bar{\varepsilon}}$ represents the average of the structural claiming elasticity calculated in the 12 months preceding the threshold.

Table A8: First-stage and Fuzzy RD estimates – Distance to closest field office

Variable	Mean (Left)	Mean (Right)	RD estimate	CI 95%	Bandwidth	Observations (Left)	Observations (Right)
A. *First-stage*							
Distance to Office (km)	34.60	14.297	-23.817***	[-39.023 -8.612]	6300.895	642	376
	Robust RD est.	Robust SD	Conventional RD est.	Conventional SD	Bandwidth	Observations (Left)	Observations (Right)
B. *Fuzzy RD estimates*							
Claimed at hometown	-0.009**	0.004	-0.010***	0.003	5849.009	571	354
Years of contribution	0.000	0.014	-0.001	0.012	5767.081	560	352
Age + Years of contribution	0.016	0.028	0.016	0.023	5846.873	575	355
Eligible to 85/95	0.000	0.002	0.001	0.002	5748.256	557	350
Pension deferral (years)	0.007	0.011	0.012	0.009	5848.146	576	354
Actuarial Replacement rate	0.001	0.001	0.001	0.001	5813.785	569	354
Actual Replacement rate	0.000	0.002	0.001	0.001	5796.241	566	354
Benefit size (BRL 2019)	1.904	7.208	1.069	6.208	5400.148	507	328
Last year employed (until 2020)	-0.002	0.009	-0.005	0.008	5461.358	516	331
Number of claims	0.323	0.275	0.240	0.234	5627.785	540	342

Note: This table presents the first-stage effect of the 20 thousand residents cutoff and reports the second-stage results for the fuzzy RD strategy using as endogenous variable P_m the distance to the closest field office. For the first-stage, I run Equation (7-3), while for the fuzzy RD I run Equation (7-4). All RD specifications use Calonico et al. (2014) and employ a linear polynomial and a triangular kernel, where the optimal bandwidth is calculated using Calonico et al. (2020). I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table A9: First stage, Differences in covariates and Fuzzy RD estimates – Before the reform

Variable	Mean (Left)	Mean (Right)	RD estimate	CI 95%	Bandwidth	Observations (Left)	Observations (Right)
A. *First-stage*							
Office at hometown	0.146	0.751	0.485***	[0.354 0.616]	6812.436	693	406
B. *Balance test*							
Male	0.610	0.654	-0.032	[-0.14 0.076]	4005.854	363	249
White	0.641	0.595	-0.008	[-0.107 0.091]	7057.229	715	411
Completed High school	0.423	0.438	-0.030	[-0.11 0.05]	6948.895	712	408
Completed College	0.084	0.098	0.009	[-0.034 0.053]	5803.433	564	363
Birth year	1957.653	1957.597	0.024	[-0.891 0.938]	5687.320	544	355
Age at eligibility	53.055	53.185	0.447	[-0.619 1.513]	5177.208	476	330
High earnings	0.342	0.374	-0.055	[-0.155 0.045]	4619.287	422	295
Avg earnings	2864.018	3224.064	-446.356	[-1172.374 279.662]	4390.206	402	278
Age at claiming	55.370	55.422	0.024	[-0.922 0.97]	5769.529	559	363
Claiming year	2013.089	2013.067	0.072	[-0.087 0.232]	7797.147	812	441
Number of claims	28.030	41.744	-13.821	[-32.837 5.194]	5551.376	526	347
	Robust		Conventional		Bandwidth	Observations	
	RD est.	SD	RD est.	SD		(Left)	(Right)
C. *Fuzzy RD estimates*							
Claimed at hometown	0.395***	0.076	0.415	0.063***	10577.781	1205	537
Years of contribution	0.083	0.672	0.120	0.587	7140.198	727	416
Age + Years of contribution	0.362	1.233	0.267	1.084	7132.457	726	415
Eligible to 85/95	-0.019	0.089	-0.027	0.076	5917.212	579	367
Pension deferral (years)	-0.335	0.353	-0.333	0.307	6967.976	710	409
Actuarial Replacement rate	0.003	0.032	0.002	0.028	6792.941	684	406
Actual Replacement rate	0.041	0.072	0.023	0.064	6523.931	669	396
Benefit size (BRL 2019)	-59.337	275.360	-13.630	233.379	5498.334	518	344
Last year employed (until 2020)	0.513	0.527	0.546	0.459	6510.371	669	394
Number of claims	-29.133	20.485	-19.199	16.707	6756.157	684	405

Note: This table presents the first-stage effect of the 20 thousand residents cutoff, checks for differences in covariate balancing and reports the second-stage results for the fuzzy RD strategy using claims from before the 2015 Reform. For the first-stage, I run Equation (7-3), while for the fuzzy RD I run Equation (7-4). All RD specifications use Calonico et al. (2014) and employ a linear polynomial and a triangular kernel, where the optimal bandwidth is calculated using Calonico et al. (2020). I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table A10: First stage, Differences in covariates and Fuzzy RD estimates – Individual-level

Variable	Mean (Left)	Mean (Right)	RD estimate	CI 95%	Bandwidth	Observations (Left)	Observations (Right)
A. *First-stage*							
Office at hometown	0.372	0.736	-0.411***	[-0.464 -0.358]	459.725	729	643
B. *Balance test*							
Male	0.589	0.637	0.003	[-0.038 0.044]	3525.065	6914	5249
White	0.818	0.803	-0.028**	[-0.052 -0.004]	4990.240	9172	8318
Completed High school	0.410	0.400	-0.012	[-0.057 0.032]	3293.217	6476	4979
Completed College	0.095	0.083	-0.012	[-0.037 0.013]	4202.329	7973	6579
Avg Earnings	2646.229	2642.906	-264.240**	[-508.039 -20.442]	3229.717	6267	4904
High Earnings	0.297	0.315	-0.069***	[-0.105 -0.033]	4179.905	7901	6510
Birth year	1962.394	1962.528	-0.362	[-0.939 0.216]	1835.024	3798	2964
Age at claiming	53.557	53.424	0.343	[-0.23 0.917]	1850.950	3799	2975
Claiming year	2015.944	2015.940	-0.022	[-0.068 0.024]	5983.408	11140	10343
Age at eligibility	50.649	50.894	0.367	[-0.259 0.993]	2022.712	4543	3133
	Robust RD est.	Robust SD	Conventional RD est.	Conventional SD	Bandwidth	Observations (Left)	Observations (Right)
C. *Fuzzy RD estimates*							
Claimed at hometown	0.385***	0.034	0.406***	0.031	3697.554	6934	5671
Years of contribution	3.305	3.855	3.075	3.813	1191.916	2419	1832
Age + Years of contribution	1.107	4.603	0.935	4.560	1014.625	2112	1711
Eligible to 85/95	-0.012	0.057	0.003	0.050	3424.227	6675	5152
Pension deferral (years)	-0.470*	0.281	-0.456*	0.266	4269.987	7993	6834
Actuarial Replacement rate	-0.525	0.950	-0.458	0.933	1360.463	2697	2098
Actual Replacement rate	0.206**	0.087	0.204**	0.085	1631.963	3535	2521
Benefit size (BRL 2019)	-269.018	226.313	-220.912	212.669	2155.009	4762	3349
Last year employed (until 2020)	-0.322	1.280	-0.296	1.271	1529.807	3522	2453

Note: This table presents the first-stage effect of the 20 thousand residents cutoff, checks for differences in covariate balancing and reports the second-stage results for the fuzzy RD strategy using claims from after the 2015 Reform at the individual-level (instead of calculating the average for each municipality). For the first-stage, I run Equation (7-3), while for the fuzzy RD I run Equation (7-4). All RD specifications use Calonico et al. (2014) and employ a linear polynomial and a triangular kernel, where I calculate the optimal bandwidth from Calonico et al. (2020) after restricting to observations from 0 to 40 thousand residents in 2007. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

B
Conceptual Framework

The conceptual framework gives an interpretation for the empirical results and guides the welfare analysis of stylized pension reforms to Early Retirement (ER). It is based on Chetty (2008), Manoli and Weber (2016) and Kolsrud et al. (2024).

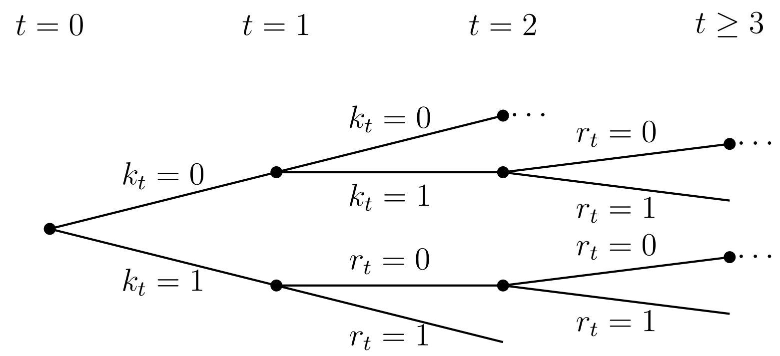
The model of individual maximization reflects the dynamic nature of the claiming and retirement decisions. Behavior is described by state-contingent value functions. Also, I consider both decisions (claiming and retirement) to be separate, although not necessarily independent. This is more consistent with countries where an individual can work while claiming social security without having benefits withheld through an earnings test.

B.1
Individual Problem

There are three main states for worker i: working (W), working and claiming a SS benefit (K) and retirement (R). Each period t represents a moment of decision making since the start of eligibility to claim retirement benefits. That is, $t = 0$ is the period in which i becomes eligible to social security, and the worker is assumed to be working. The terminal period T represents death. The model is written so that the agent transitions between states if her claiming or working disulities become higher than reservation disutilies derived in the model solution.

An important aspect of claiming and retirement decisions is their sequential nature. The model is written to represent the decision of an agent who has a say on when to drop out of the workforce. That is, dismissal risks are accommodated in the model through work and pension deferral disutilities, but not through a risk of becoming unemployed in the following period. Therefore, I assume that the agent first decides when to claim a pension, and then whether to leave the workforce or not. This ensures that the agent does not transition directly from working to retired, which is reasonable in the context of early retirement and for arbitrarily short periods.

Figure B1: Decision tree for claiming and retirement decisions



Note: This figure depicts the decision tree of a worker whose individual problem is described in Section 2.1 by the value functions (2-1), (2-2) and (2-3). Once eligibility to claim an early retirement pension is achieved, the worker sequentially decides when to claim the pension and when to leave the workforce.

At each period t since eligibility, the agent makes two decisions. First, she chooses consumption for period t (analogous to choosing assets for $t+1$). Second, the agent decides whether to transition or not to the next state (K or R) in the following period, given her expectation of next period's state-contingent utility.

The policy parameter in the model is the pension schedule $B = \{b_j\}_{j=0}^{T}$. The labor income tax τ is assumed to be exogenous. The pension schedule represents the amount of benefits gained by each period j of claiming deferral.

I remove the i superscript in the following for clarity.

B.1.1
Pension schedule

In early retirement systems, the benefit amount depends on how far away the individual is from the Normal Retirement Age (NRA). That is, the pension schedule generates financial incentives to postpone benefit claiming through a higher replacement rate[1]. Once i claims the benefit, the amount is the same for the rest of her life. This permanent reduction in the replacement rate of early retirement benefits is a common feature of countries with early retirement pensions, either due to actuarial fairness and/or to the embedding of financial incentivesin the benefit schedule.

I consider such financial incentives in the model. At each period t, i is eligible to claim a benefit $b(t)$ which is increasing with t. If the agent claimed

[1] In Brazil, each month an individual postpones the claim implies a higher *fator previdenciário*, which is the replacement rate of the benefit. In the US, each month further from the NRA implies a benefit reduction of $\approx 0.56\%$.

her pension at period κ, then her monthly benefit for the rest of her life will be $b(\kappa)$.

B.1.2 Uncertainty

The uncertainty in the decision-making stems from both the disutility of postponing benefit claiming and the disutility of working. The disutility of deferral encompasses the trade off between having a guaranteed income through old-age benefits — which would allow for consumption smoothing in the event of job displacement —, and increasing the lifetime pension wealth — given the positive slope of the pension schedule[2]. That is, the disutility of pension deferral is an opportunity cost for postponing an annuity. Being eligible to a benefit and yet choosing to postpone its claim has costs in the form of impatience and reduced present consumption. Both disutilities are stochastic processes which depend on past realizations and on present shocks ν_t, for deferral, and ψ_t, for working. Therefore, i cannot completely anticipate her next-period utility if she decides to postpone claiming or retirement. Disutility shocks are given by realizations of the distributions $Q(\cdot)$ and $L(\cdot)$, with parameters $\zeta^i \in Z$ and $\theta^i \in \Theta$.

Formally, the disutility of pension deferral and of working at t are given by:

$$\begin{cases} \phi_t = \rho\phi_{t-1} + \nu_t, \text{ where } \nu_t \sim Q(\zeta) \\ \alpha_t = \rho\alpha_{t-1} + \psi_t, \text{ where } \psi_t \sim L(\theta) \end{cases}$$

B.1.3 Choice and state variables

The budget set for the individual in each possible state is given by:

$$\begin{cases} c_t^W + R_{t+1}a_{t+1} \leq R_t a_t + w(1-\tau) \\ c_t^K + R_{t+1}a_{t+1} \leq R_t a_t + w(1-\tau) + b(\kappa) \\ c_t^R + R_{t+1}a_{t+1} \leq R_t a_t + b(\kappa) \end{cases}$$

Where w is labor income, R_t is the gross interest rate (which I assume to be equal to 1 for simplicity), τ is labor income taxation, a_t are assets, c_t^j is consumption in state $j \in \{W, K, R\}$ and κ is the period in which i claimed the benefit.

At each period t, i chooses the assets and the transition between states for the next period: $k_t = \mathbb{1}(\text{claim at } t+1)$ and $r_t = \mathbb{1}(\text{retire at } t+1)$. The

[2]However, whether an additional year of deferral increases lifetime SS wealth depends on the steepness of the pension schedule, since it implies fewer years receiving the pension.

state variables considered for these decisions are the assets and the disutility of working and deferral shocks in previous periods. The state variables in period t are summarized by $\Omega_t = (\{a_j\}_{j=0}^t, \{\nu_j\}_{j=0}^t, \{\psi_j\}_{j=0}^t)$.

B.1.4
Value functions

The individual problem is described by the following set of value functions:

– From working and not claiming t periods after eligibility:

$$V_t^W(\Omega_t) = \max_{a_{t+1}} u(R_t a_t - R_{t+1}a_{t+1} + w(1-\tau)) - \phi_t - \alpha_t + \beta \mathbb{E}_t\Big[\max_{k_t\in\{0,1\}} k_t V_{t+1}^K(\Omega_{t+1}) + (1-k_t)V_{t+1}^W(\Omega_{t+1})\Big] \quad \text{(B-1)}$$

– From working and claiming t periods after eligibility:

$$V_t^K(\Omega_t) = \max_{a_{t+1}} u(R_t a_t - R_{t+1}a_{t+1} + w(1-\tau) + b(\kappa)) - \alpha_t + \beta \mathbb{E}_t\Big[\max_{r_t\in\{0,1\}} r_t V_{t+1}^R + (1-r_t)V_{t+1}^K(\Omega_{t+1})\Big] \quad \text{(B-2)}$$

where $\kappa = min_j(\{j \geq 0 : k_j = 1\})$

– From being retired t years after eligibility:

$$V_t^R = \max_{a_{t+1}} u(R_t a_t - R_{t+1}a_{t+1} + b(\kappa)) + \beta V_{t+1}^R \quad \text{(B-3)}$$

The individual expected lifetime utility for a given state stream Ω and a pension schedule $B = \{b_j\}_{j=0}^T$ is then given by $\mathcal{U}^e(\Omega) \equiv V_{t=0}^W(\Omega)$.

B.2
Optimal strategy

In this model, the optimal strategies of claiming and retirement are described by reservation disutilities $\bar{\phi}_t$ and $\bar{\alpha}_t$ such that:

$$\begin{cases} \phi_t > \bar{\phi}_t \Rightarrow k_t = 1 \\ \alpha_t > \bar{\alpha}_t \Rightarrow r_t = 1 \end{cases}$$

I make the following assumption to simplify the optimal strategy:

Assumption 1 *Claiming and retirement are sequential decisions.*

Assumption 1 implies that the agent cannot transition directly from working to retirement. Essentially, this assumption implies that the trade-off in claiming deferral at each period implicitly assumes away the future trade-off between working and retirement that will be faced by the agent. This seems reasonable in the context of early retirement and for arbitrarily short periods. Appendix Figure C2 plots the probability of employment for different groups of claiming ages and provides suggestive evidence that this assumption might hold especially for younger claimants, whose probability of employment barely decreases at the claiming semester. The claiming decision is greatly simplified since the agent compares her value for working an additional period to her value of start claiming in the following period — abstracting from her value of retiring.

B.2.1 Claiming decision

Under Assumption 1, for a given period t, the reservation deferral disutility is given by:

$$
\begin{aligned}
&V_t^W(\Omega_t(\bar{\phi}_t)) = V_t^K(\Omega_t) \iff \\
&\quad \iff u(a_t - a_{t+1} + w(1-\tau)) - \bar{\phi}_t - \alpha_t + \beta \mathbb{E}_t \max\{V_{t+1}^K, V_{t+1}^W\} = \\
&\qquad u(a_t - a_{t+1} + w(1-\tau) + b(t)) - \alpha_t + \beta \mathbb{E}_t \max\{V_{t+1}^K, V_{t+1}^R\} \\
&\quad \iff \bar{\phi}_t = u(a_t - a_{t+1} + w(1-\tau)) - u(a_t - a_{t+1} + w(1-\tau) + b(t)) + \\
&\qquad\qquad \beta \mathbb{E}_t\{\max(V_{t+1}^W, V_{t+1}^K) - \max(V_{t+1}^R, V_{t+1}^K)\}
\end{aligned}
$$

Consider a first-order Taylor approximation of $u(\cdot)$ around $a_t - a_{t+1} + w(1-\tau)$:

$$u(a_t - a_{t+1} + w(1-\tau) + b(t)) \approx u(a_t - a_{t+1} + w(1-\tau)) + u'(a_t - a_{t+1} + w(1-\tau))b(t)$$

Then, the reservation disutility of deferral is given by:

$$\bar{\phi}_t \approx -u'(a_t - a_{t+1} + w(1-\tau))b(t) + \beta OV_t^K \tag{B-4}$$

where $OV_t^K \equiv \mathbb{E}_t\{\max(V_{t+1}^W, V_{t+1}^K) - \max(V_{t+1}^R, V_{t+1}^K)\}$ is the option-value from delaying the claim of social security benefits. This option-value highlights that the opportunity cost from claiming a benefit at t is the possibility to claim higher pensions in future periods, but at the risk of higher work and deferral disutilities and at the cost of fewer accrual periods. Note that OV_t^K is not necessarily positive:

(i)	$\mathbb{E}_t V_{t+1}^R > \mathbb{E}_t V_{t+1}^W > \mathbb{E}_t V_{t+1}^K$	$\Rightarrow OV_t^K < 0$	(iv)	$\mathbb{E}_t V_{t+1}^K > \mathbb{E}_t V_{t+1}^R > \mathbb{E}_t V_{t+1}^W$	$\Rightarrow OV_t^K = 0$
(ii)	$\mathbb{E}_t V_{t+1}^W > \mathbb{E}_t V_{t+1}^R > \mathbb{E}_t V_{t+1}^K$	$\Rightarrow OV_t^K > 0$	(v)	$\mathbb{E}_t V_{t+1}^W > \mathbb{E}_t V_{t+1}^K > \mathbb{E}_t V_{t+1}^R$	$\Rightarrow OV_t^K > 0$
(iii)	$\mathbb{E}_t V_{t+1}^K > \mathbb{E}_t V_{t+1}^W > \mathbb{E}_t V_{t+1}^R$	$\Rightarrow OV_t^K = 0$	(vi)	$\mathbb{E}_t V_{t+1}^R > \mathbb{E}_t V_{t+1}^K > \mathbb{E}_t V_{t+1}^W$	$\Rightarrow OV_t^K < 0$

B.2.2
Retirement decision

For a given period t, the reservation work disutility is given by:

$$
\begin{aligned}
&V_t^K(\Omega_t(\bar{\alpha}_t)) = V_t^R(\Omega_t) \iff \\
&\quad \iff u(a_t - a_{t+1} + w(1-\tau) + b(t)) - \bar{\alpha}_t + \beta \mathbb{E}_t \max\{V_{t+1}^K, V_{t+1}^R\} = \\
&\qquad\qquad u(a_t - a_{t+1} + b(t)) + \beta V_{t+1}^R \\
&\quad \iff \bar{\alpha}_t = u(a_t - a_{t+1} + w(1-\tau) + b(t)) - u(a_t - a_{t+1} + b(t)) + \\
&\qquad\qquad \beta\{\mathbb{E}_t \max(V_{t+1}^K, V_{t+1}^R) - V_{t+1}^R\}
\end{aligned}
$$

Consider a first-order Taylor approximation of $u(\cdot)$ around $a_t - a_{t+1} + b(t)$:

$$
u(a_t - a_{t+1} + w(1-\tau) + b(t)) \approx u(a_t - a_{t+1} + b(t)) + u'(a_t - a_{t+1} + b(t))w(1-\tau)
$$

Then, the reservation disutility is given by:

$$
\bar{\alpha}_t \approx u'(a_t - a_{t+1} + b(t))w(1-\tau) + \beta OV_t^R \tag{B-5}
$$

where $OV_t^R \equiv \mathbb{E}_t \max(V_{t+1}^K, V_{t+1}^R) - V_{t+1}^R$ is the option-value from not retiring at t. This option-value highlights that the opportunity cost from retiring at t is the foregone labor income from additional periods in the labor force, at the risk of a higher work disutility. Note that $OV_t^R \geq 0$ since $OV_t^R \equiv \mathbb{E}_t\{\max(V_{t+1}^R, V_{t+1}^K) - V_{t+1}^R\} \geq 0$

B.2.3
Heterogeneity

The model allows for heterogeneity across individuals not only through the parameters ζ^i and θ^i, but also through different individual realizations of the disutility shocks ν_t and ψ_t. For example, an individual with bad health might have both a higher ζ and a higher θ, which then implies that her disutility shocks increase rapidly. It will end up being optimal for her to claim benefits early and to leave the workforce early as well. There could also be a very risk-averse individual. In this case, her ζ would be high, but θ could vary freely. This implies that she will claim her benefit early to ensure consumption smoothing in the following period, but she might retire well beyond in the future.

B.2.4
Claiming and Retirement distributions

Given the reservation disutilities, I characterize the distributions of claiming and retirement across periods t for the population. The claiming hazard and the labor market exit distribution are given by:

$$\textbf{Claiming hazard:} \quad CH(t;B) \equiv \Pr(i \text{ claims at } t \mid i \text{ has not yet claimed}) =$$
$$= \Pr(\phi_t \geq \bar{\phi}_t \mid \phi_{t-1} < \bar{\phi}_{t-1})$$
$$= \Pr\Big(\phi_t \geq -u'(a_t - a_{t+1} + w(1-\tau))b(t) + \beta OV_t^K \mid \phi_{t-1} < \bar{\phi}_{t-1}\Big) \quad \text{(B-6)}$$

From the claiming hazard rates at 0, ..., t, I characterize the CDF of pension claiming for each period after eligibility, $D(t;B) = \Pr(i \text{ has claimed at } t)$. For simplicity, I omit the pension schedule $B = (b_0, ..., b_T)$, which is the set of policy parameters.

$$\textbf{Retirement distribution:} \quad S(t;B) \equiv \Pr(i \text{ is retired at } t \mid i \text{ has not yet retired})$$
$$= \Pr(\alpha_t \geq \bar{\alpha}_t \mid \phi_{t-1} \geq \bar{\phi}_{t-1})$$
$$= \Pr\Big(\alpha_t \geq u'(a_t - a_{t+1} + b(t))w(1-\tau) + \beta OV_t^R \mid \phi_{t-1} \geq \bar{\phi}_{t-1}\Big) \quad \text{(B-7)}$$

B.3
Model Predictions

Next, I use the model to interpret how changes in the pension schedule affect the claiming and retirement decisions. Consider $\Delta b_p > 0$, for $p > 0$. That is, an increase in the gain from postponing claiming at period p, which increases the steepness of the pension schedule.

B.3.1
Effect on Claiming

i. $\underline{t \leq p-1}$: $\Delta b_p > 0 \Rightarrow \downarrow \Pr(\phi_t \geq \bar{\phi}_t)$ and $\frac{\partial CH(t)}{\partial b_p} \leq 0$ through a substitution effect:

$$\frac{\partial \bar{\phi}_t}{\partial b_p} = \beta \frac{\partial OV_t^K}{\partial b_p}, \text{ since } \frac{\partial b(t)}{\partial b_p} = 0$$

$$\text{But } \frac{\partial V_{t+1}^W}{\partial b_p} > 0 \text{ and } \frac{\partial V_{t+1}^K}{\partial b_p} = \frac{\partial V_{t+1}^R}{\partial b_p} = 0. \text{ Then, } \frac{\partial OV_t^K}{\partial b_p} \geq 0$$

The decrease in the claiming hazard is interpreted as a substitution effect since, by increasing the steepness of the schedule, the price of claiming today relative to the price of claiming in future periods has changed, which is captured in the option-value of claiming. There is no income effect, however, since there is no change in the wealth of the agent at t.

ii. $\underline{t > p-1}$: $\Delta b_p > 0 \Rightarrow \uparrow \Pr(\phi_t \geq \bar{\phi}_t)$ and $\frac{\partial CH(t)}{\partial b_p} > 0$ through an income effect:

$$\frac{\partial b(t)}{\partial b_p} > 0 \Rightarrow \uparrow u'(a_t - a_{t+1} + w - \tau)b(t) \Rightarrow \frac{\partial \bar{\phi}_t}{\partial b_p} < 0$$

The option-value of claiming $OV_t^K = \mathbb{E}_t\{\max(V_{t+1}^W, V_{t+1}^K) - \max(V_{t+1}^R, V_{t+1}^K)\}$ could also change. However, V_{t+1}^W, V_{t+1}^K, V_{t+1}^R increase jointly through the marginal utility of consumption, implying that any change to the option-value is only an income effect . The increase in the claiming hazard is interpreted as an income effect since, after period p, there is no change in relative prices of claiming for the agent.

B.3.2 Effect on Retirement

i. $\underline{t \leq p-1}$: $\Delta b_p > 0 \Rightarrow$ $\Pr(\alpha_t \geq \bar{\alpha}_t)$ is unchanged and $\frac{\partial S(t)}{\partial b_p} = 0$:

This is the case since $\dfrac{\partial V_{t+1}^K}{\partial b_p} = \dfrac{\partial V_{t+1}^R}{\partial b_p} = 0 \Rightarrow \dfrac{\partial OV_t^R}{\partial b_p} = 0$ and $\dfrac{\partial b(t)}{\partial b_p} = 0$

Intuitively, if there is an increase of pension benefits for those who claim after period p, those who have already claimed before p are not affected through substitution or income effects.

ii. $\underline{t > p-1}$: $\Delta b_p > 0 \Rightarrow$ $\uparrow \Pr(\alpha_t \geq \bar{\alpha}_t)$ and $\frac{\partial S(t)}{\partial b_p} > 0$ through an income effect:

$$\frac{\partial b(t)}{\partial b_p} > 0 \Rightarrow \downarrow u'(a_t - a_{t+1} + b(t))w(1-\tau), \text{ if } u''(\cdot) < 0. \text{ Then, } \frac{\partial \bar{\alpha}_t}{\partial b_p} < 0$$

Remember that the option-value of retirement OV_t^R is a trade-off between the net-wage $w(1-\tau)$ and the expected disutility from working — which are unchanged. This change in benefit will increase V_{t+1}^R and V_{t+1}^K jointly though the marginal utility of consumption, and any change in OV_t^R will capture solely the change in marginal utilities. Therefore, the model predicts that a steeper pension profile affects the retirement decision only through an income effect. The amount of pension benefits will impact this decision only by increasing the agent's wealth: with increased wealth, she might retire earlier. Hence, any changes in retirement are driven purely by an income effect.

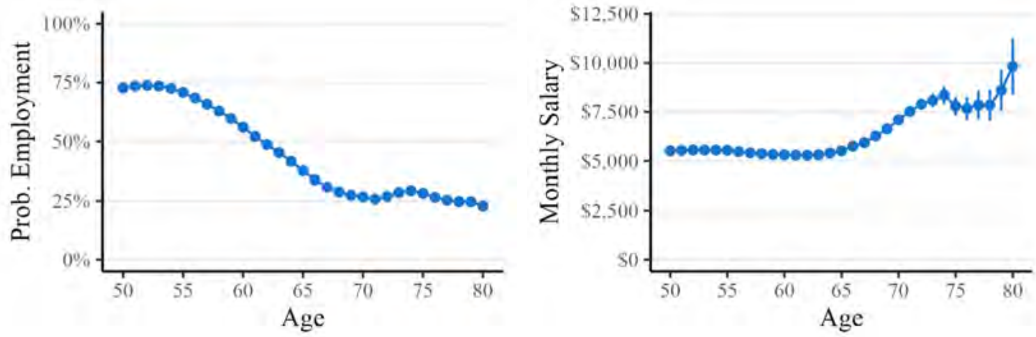
B.3.3
Sufficient Statistics

The model predictions hint what should be the sufficient statistics for a Welfare analysis of pension reforms under the assumption of sequential claiming and retirement decisions. Such parameters are the price/substitution and income elasticities of claiming with respect to benefits and the income elasticity of retirement with respect to benefits.

C
Background

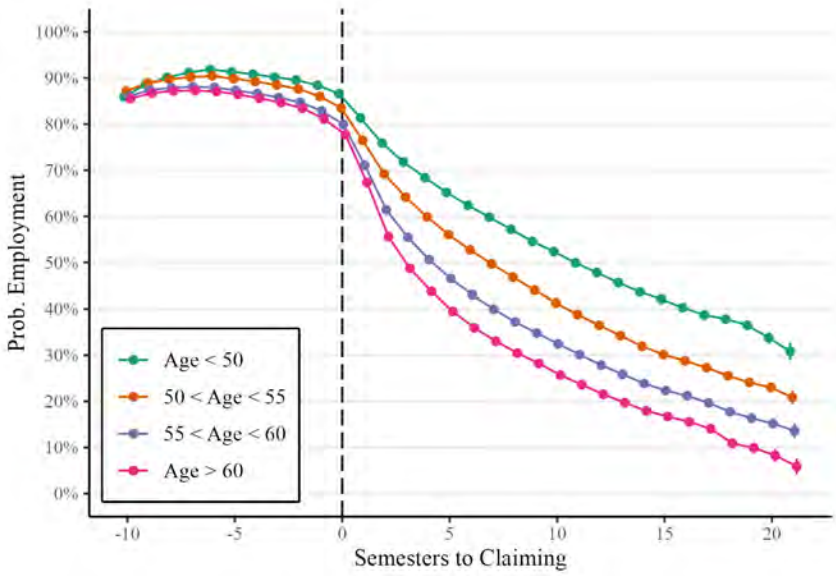
Figure C1: Trends for employment and earnings (conditional on formal job) by age

A. Prob. employment **B.** Earnings (BRL 2019)



Note: This figure plots the trends for formal employment and labor earnings by age, for all individuals in the SUIBE-RAIS full sample. I also present 95% confidence intervals for the averages.

Figure C2: Trends for employment by age at claiming



Note: This figure plots the trends for employment by distance to the claiming semester, where I separate individuals in the SUIBE-RAIS full sample by age at the claiming semester.

Table C1: Summary statistics (ELSI-Brazil)

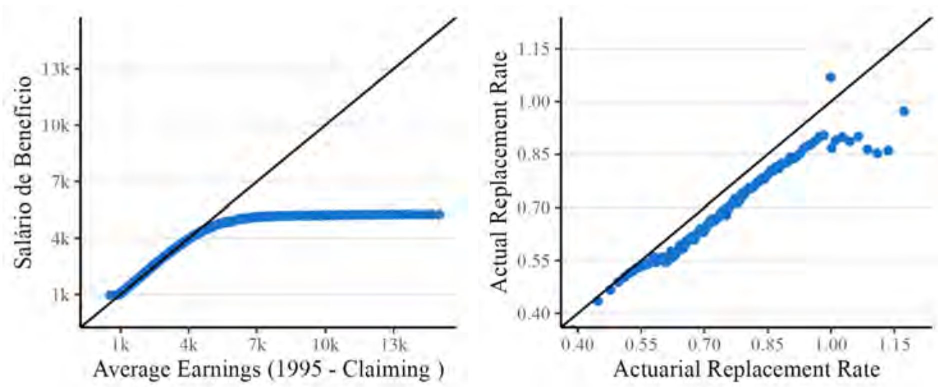
	All	Gender		Pension type					
		Men	Women	None	Rural	Full Ret.	Early Ret.	Disability	Low-inc.
A. *Demographics*									
Male	0.472	1.000	0.000	0.445	0.417	0.377	0.590	0.663	0.330
Age	63.317	63.332	63.304	58.567	67.782	73.456	66.885	63.686	60.757
Household size	2.489	2.516	2.465	2.555	2.521	2.332	2.362	2.450	2.686
Receives BPC/BF pension	0.069	0.050	0.086	0.000	0.030	0.062	0.009	0.043	1.000
White	0.464	0.468	0.460	0.443	0.469	0.478	0.551	0.471	0.297
Number of children	3.129	3.053	3.197	2.730	4.452	4.041	2.806	2.633	3.721
Mother was schooled	0.435	0.450	0.422	0.491	0.261	0.328	0.514	0.423	0.300
Father was schooled	0.482	0.492	0.472	0.530	0.307	0.409	0.562	0.458	0.358
Completed Elementary school	0.672	0.674	0.670	0.758	0.389	0.505	0.794	0.625	0.525
Completed High school	0.236	0.229	0.242	0.275	0.073	0.135	0.358	0.167	0.135
Completed college	0.061	0.054	0.067	0.057	0.022	0.033	0.136	0.040	0.017
Good health	0.479	0.488	0.470	0.524	0.415	0.413	0.575	0.253	0.369
Was in school at 10 y.o.	0.750	0.748	0.751	0.810	0.585	0.621	0.816	0.721	0.656
B. *Consumption and assets*									
Household Consumption	1263.089	1308.473	1222.496	1276.455	980.734	1083.158	1691.958	1120.778	859.827
Consumption per capita	580.338	587.328	574.085	567.991	454.334	540.949	802.712	516.042	366.335
Owns a house	0.851	0.854	0.848	0.820	0.911	0.888	0.883	0.847	0.805
Owns a car	0.380	0.450	0.318	0.417	0.276	0.273	0.495	0.342	0.174
Has a computer	0.276	0.287	0.267	0.315	0.120	0.172	0.381	0.250	0.168
Has internet access	0.947	0.958	0.937	0.944	0.896	0.929	0.984	0.912	0.919
Has private health insurance	0.197	0.197	0.196	0.173	0.107	0.185	0.358	0.196	0.060
C. *Retirement-related*									
Age at claiming	56.601	56.613	56.589	56.031	56.001	64.296	55.522	49.823	62.573
Pension size	1770.399	1964.363	1599.571	1743.094	1343.201	1371.942	2354.355	1598.742	1142.550
Receives any pension	0.513	0.512	0.513	0.141	0.896	0.892	0.938	0.904	0.039
Receives old-age pension	0.492	0.533	0.455	0.007	1.000	1.000	1.000	1.000	0.010
Pension is from INSS	0.815	0.847	0.782	0.839	0.660	0.868	0.836	0.909	0.415
Receives private pension	0.049	0.063	0.034	0.038	0.021	0.045	0.069	0.047	0.000
D. *Work-related*									
Is employed	0.310	0.395	0.234	0.497	0.119	0.122	0.202	0.067	0.244
Labor earnings	1690.521	1892.784	1392.592	1726.361	1441.710	1342.798	2152.442	1177.725	607.284
Receives capital income	0.054	0.064	0.045	0.058	0.033	0.038	0.079	0.047	0.024
Household income	2967.582	3114.096	2837.124	2857.857	2524.392	2597.391	4172.840	2812.593	1751.299
Has ever worked	0.843	0.930	0.765	0.857	0.640	0.813	0.953	0.865	0.795
Age when started working	16.009	14.752	17.394	16.221	15.681	16.590	15.551	15.302	16.397
Is still working	0.415	0.480	0.343	0.662	0.163	0.165	0.222	0.049	0.417
Age when stopped working	51.665	55.132	48.617	43.457	54.312	60.699	55.813	48.583	48.592
Was an informal worker	0.366	0.304	0.433	0.409	0.496	0.435	0.169	0.279	0.538
Was a formal worker	0.500	0.555	0.439	0.431	0.252	0.468	0.767	0.642	0.292
Was self-employed	0.128	0.135	0.121	0.153	0.238	0.091	0.061	0.075	0.157
Was full-time worker	0.818	0.845	0.790	0.823	0.824	0.797	0.824	0.814	0.797
Worked in the last 12 months	0.383	0.441	0.320	0.616	0.141	0.149	0.228	0.049	0.309
Contributes to social security	0.329	0.404	0.273	0.353					0.097
Is a care-giver	0.126	0.080	0.168	0.142	0.098	0.084	0.120	0.099	0.195
E. *Regional*									
North region	0.067	0.067	0.066	0.075	0.077	0.084	0.033	0.027	0.111
Northeast region	0.282	0.286	0.278	0.261	0.457	0.257	0.208	0.252	0.450
Southeast region	0.432	0.437	0.429	0.463	0.244	0.428	0.489	0.452	0.343
South region	0.133	0.126	0.140	0.111	0.155	0.120	0.203	0.150	0.041
Central-west region	0.086	0.085	0.087	0.090	0.067	0.111	0.066	0.119	0.055
F. *Satisfaction and plans*									
Current income is insufficient	0.341	0.336	0.346	0.371	0.294	0.323	0.246	0.323	0.576
Is satisfied with retirement	0.719	0.666	0.775	0.495	0.867	0.761	0.642	0.637	1.000
When expects to claim pension	61.948	62.328	61.561	62.029					61.059
Plans to work after retirement	0.241	0.330	0.162	0.250					0.154
Has own savings for retirement	0.045	0.059	0.032	0.046	0.024	0.029	0.072	0.040	0.023
Expects family help after ret.	0.085	0.071	0.097	0.081	0.091	0.093	0.083	0.079	0.099
Has planned for the future	0.204	0.215	0.195	0.164	0.216	0.292	0.243	0.262	0.143
G. *Other*									
Was victim of a crime	0.055	0.053	0.057	0.059	0.062	0.056	0.039	0.046	0.075
Wishes to move out	0.164	0.146	0.181	0.185	0.096	0.136	0.146	0.180	0.229
Observations	9,949	4,144	5,805	3,786	1,363	1,572	1,928	785	515

Note: This table presents summary statistics from the ELSI-Brazil using the calibrated survey weights. I present averages for the whole sample, as well as separating respondents by gender and pension type.

Figure C3: *Salário de benefício*, Average Earnings and Replacement rates

A. *Salário de benefício* by average earnings

B. Actual *VS* Actuarial Replacement rates



Note: This figure presents more details on the relationship between the actual and actuarial replacement rates. As discussed in Section 3, the assessment basis used to calculate the pension size a worker is eligible to claim is capped on the lower end by the minimum age and at the upper end by the *teto previdenciário*. While the minimum wage is generally adjusted above the yearly inflation, this upper cap is adjusted each year by the accumulated inflation over the previous 12 months. Therefore, the INSS calculates for each worker the assessemnt basis (known as *salário de benefício*) by averaging the 80% highest capped monthly wages a worker received from July 1994 to the claiming day. Panel A presents the binscatter plot for the *salário de benefício* by the average uncapped earnings. Furthermore, I term actuarial replacement rate as the *fator previdenciário*, which represents the share of the *salário de benefício* an indiviual receives as social security benefit. Meanwhile, the actual replacement rate represents the share of the average uncapped earnings an individual receives as monthly benefit. Panel B depicts the binscatter plot for the actual replacement rate by the actuarial replacement rate.

D
Data

D.1
Data access

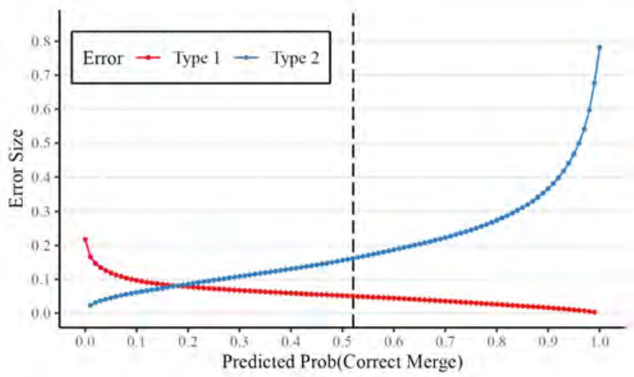
1. SUIBE PDA is publicly available through the *Plano de Dados Abertos* 2023/2025 (PDA) program from INSS. However, I also requested additional information on years of contribution under a *Lei de Acesso à Informação* request to INSS (Protocol number 18800.199973/2024-12).

2. SUIBE LAI was requested under a *Lei de Acesso à Informação* request to INSS (Protocol number 36783.008391/2023-92). The publicly available dataset does not inform on the partial tax identifier number.

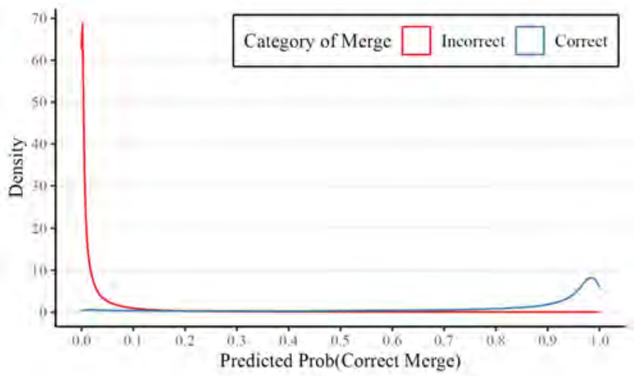
3. ELSI-Brazil is publicly available to all researchers on the project's website. "ELSI-Brazil was funded by the Ministry of Health: DECIT/SCTIE – Department of Science and Technology of the Secretary of Science, Technology, and Strategic Inputs (Processes: 404965/2012-1 and TED 28/2017); COPID/DECIV/SAPS – Coordination of Health for the Elderly in Primary Care, Department of Life Cycles of the Secretariat of Primary Health Care (Processes: 20836, 22566, 23700, 25560, 25552, and 27510). ELSI-Brazil was approved by the Fundação Oswaldo Cruz (FIOCRUZ) ethics committee, Minas Gerais, Brazil (protocol number 34649814.3.0000.5091)."

Figure D1: Estimating the probability of correct merge – Results

A. Errors Type 1 and 2 for each cutoff

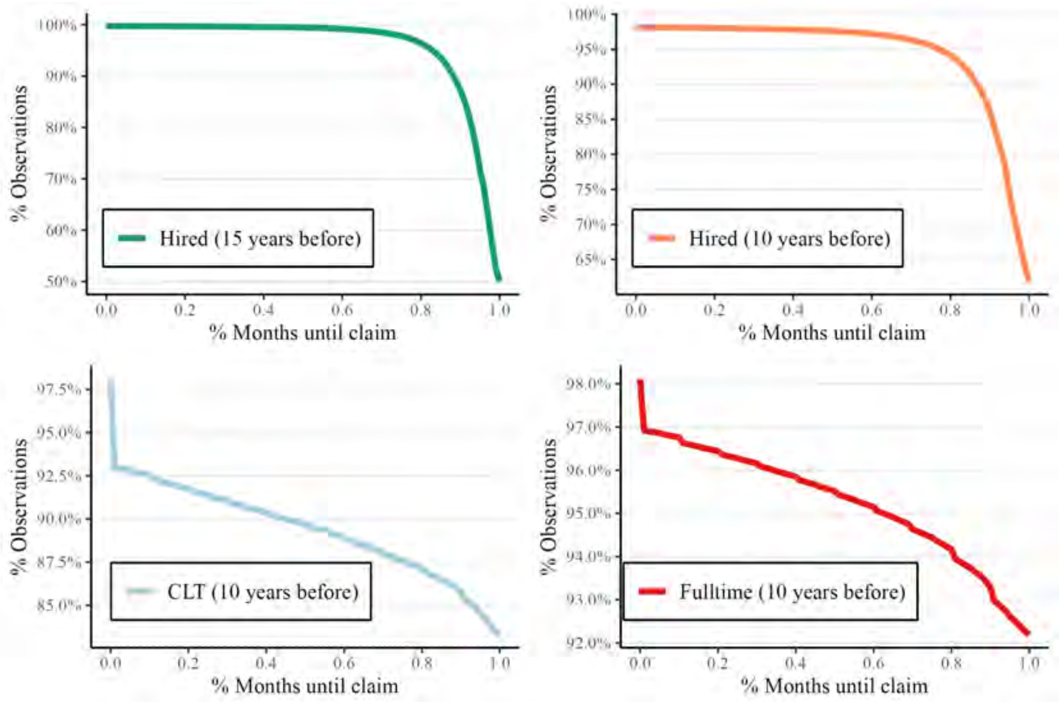


B. Predicted probability of correct merge



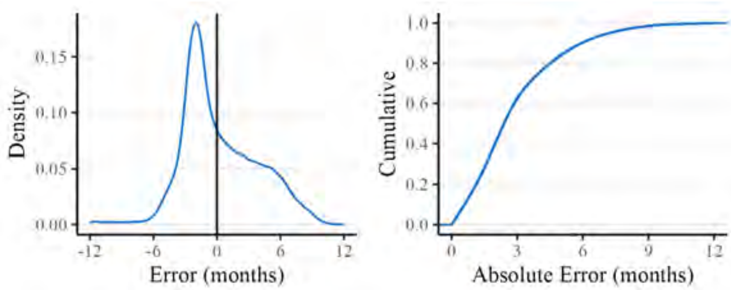
Note: This figure depicts the results for the estimation of the probability of a correct merge. As detailed in Section 3, I merge the 370 thousand individuals in the SUIBE dataset whose full CPF I observe to a cross-section derived from RAIS (2003–2020). I employ the partial CPF (3 digits), the gender and the date of birth, which expectadly produces several non-uniquely identified matches. To address this issue, I estimate a Logit model that predicts which merges are correct based on observable characteristics, such as the municipality of residence over different time horizons and whether the individual was reported in RAIS to have retired. Appendix Table D2 presents the results for alternative models where I gradually include fixed-effects into the specification. The Logit models perform very well in predicting which merges are correct based on the observables, with an R-squared equal to 0.691 when I include all fixed-effects. Additionally, I merge these individuals to the RAIS cross-section using the full CPF information, which uniquely identifies individuals in both datasets. This allows me to calculate the share of workers I exclude from the final dataset once I restrict to observations above a certain cutoff for the predicted probability of being a correct merge. Hence, I can calculate both the error type I and error type II associated with my merge procedure for each possible cutoff. Panel A depicts these error sizes for each possible cutoff. As I increase the strictness of the merge, the error type I decreases. However, decreasing the leniency also excludes potential matches from the dataset, resulting in a higher error type II. Panel B plots the density of the predicted probability of being a correct merge in the full matched dataset of SUIBE and RAIS, which features several non-uniquely identified individuals. Reassuringly, incorrect matches have the lowest probability of being a correct merge, while correct matches are on the upper end of the distribution. I choose a cutoff for the predicted probability of being a correct merge equal to 0.51 (the dashed black line), which ensures an error type I of 5% and has an associated error type II of 16.1%.

Figure D2: Sample selection – Descriptive statistics



Note: This figure provides descriptive statistics on the sample selection procedure. For each panel, I plot the share y of observations in the matched SUIBE-RAIS dataset that present a given characteristic for at least x percent of the months preceding the claiming period. For example, Panel A depicts the share of workers who are formally employed for at least x% of the 180 months preceding the claiming month (15 years), while Panel B plots the share who are employed for at least x% of the 120 previous months (10 years). Additionally, Panel C presents the share of observations with private-sector formal jobs (CLT type) for at least x% of the 15 previous years, and Panel D plots the share with full-time jobs (above 30 weekly hours) for at least x% of the same period. I restrict the SUIBE-RAIS to workers who were employed for at least 60% of the 10 years preceding the claiming period, had a private-sector formal job type for at least 20% of their employment period before claiming, and were full-time workers for at least 20% of their employment period before claiming.

Figure D3: Estimating the continuous years of contribution



Note: The SUIBE dataset informs the continuous years of contribution (including months and days) only for workers who claimed their pensions after July 2015. For those who claimed before this period, I can only observe their discrete years of contribution. Hence, I use those who claimed after this period to estimate the continuous years of contribution before July 2015 in an OLS model with fixed-effects, based on several observables. This figure presents the model fit by plotting the density and cumulative distributions of the residuals (in months) between the estimated continuous years of contribution and the observed years of contribution. Reassuringly, this model performs well in predicting the continuous years of contribution for those who claimed their pension after July 2015.

Table D1: Balance check for merge procedures

	Merging SUIBEs LAI and PDA									Merging SUIBE and RAIS		
	SUIBE PDA				SUIBE LAI							
Variable	Full	Unique	Duplicated	Unique – Dupl	Full	Unique	Duplicated	Unique – Dupl	Merged SUIBE	Merged w/ RAIS	Not merged	Difference
Has full CPF					0.211	0.191	0.263	-0.072	0.191	0.182	0.208	-0.026
					(0.408)	(0.393)	(0.440)		(0.393)	(0.386)	(0.406)	
Actuarial Replacement rate					0.732	0.731	0.734	-0.003	0.731	0.723	0.747	-0.024
					(0.145)	(0.155)	(0.106)		(0.155)	(0.154)	(0.156)	
Claiming year	2014.979	2014.877	2015.245	-0.368	2015.100	2015.043	2015.247	-0.205	2015.046	2015.102	2014.933	0.169
	(3.007)	(3.254)	(2.209)		(2.681)	(2.843)	(2.198)		(2.842)	(2.736)	(3.039)	
Birth year	1960.310	1960.492	1959.833	0.658	1960.063	1960.156	1959.824	0.331	1960.157	1960.606	1959.260	1.347
	(6.024)	(6.624)	(3.999)		(5.001)	(5.345)	(3.962)		(5.343)	(5.232)	(5.449)	
Male	0.638	0.627	0.668	-0.041	0.644	0.634	0.668	-0.034	0.634	0.631	0.641	-0.011
	(0.480)	(0.484)	(0.471)		(0.479)	(0.482)	(0.471)		(0.482)	(0.483)	(0.480)	
Age at claiming	54.697	54.417	55.434	-1.017	55.028	54.881	55.409	-0.528	54.920	54.527	55.705	-1.178
	(6.137)	(6.847)	(3.556)		(4.538)	(4.876)	(3.490)		(4.874)	(4.837)	(4.852)	
State capital	0.296	0.286	0.323	-0.038					0.286	0.298	0.261	0.037
	(0.456)	(0.452)	(0.468)						(0.452)	(0.457)	(0.439)	
Judicialized issuance	0.163	0.220	0.014	0.206					0.223	0.242	0.185	0.058
	(0.369)	(0.414)	(0.116)						(0.416)	(0.429)	(0.388)	
Central-west region	0.035	0.034	0.038	-0.004					0.034	0.038	0.026	0.013
	(0.184)	(0.181)	(0.192)						(0.182)	(0.192)	(0.158)	
Northeast region	0.110	0.108	0.114	-0.006					0.108	0.124	0.074	0.050
	(0.313)	(0.311)	(0.318)						(0.310)	(0.330)	(0.262)	
North region	0.017	0.017	0.018	-0.001					0.017	0.020	0.010	0.010
	(0.129)	(0.128)	(0.131)						(0.128)	(0.140)	(0.099)	
Southeast region	0.581	0.565	0.622	-0.056					0.564	0.525	0.644	-0.119
	(0.493)	(0.496)	(0.485)						(0.496)	(0.499)	(0.479)	
South region	0.257	0.276	0.209	0.067					0.277	0.293	0.246	0.046
	(0.437)	(0.447)	(0.406)						(0.448)	(0.455)	(0.431)	
Urban resident	0.996	0.996	0.996	0.000					0.996	0.995	0.997	-0.002
	(0.064)	(0.064)	(0.066)						(0.064)	(0.069)	(0.052)	
Population size in 2010	1881719.978	1808833.566	2073638.337	-264804.771					1813364.262	1715783.629	2008405.305	-292621.676
	(3473933.907)	(3412755.700)	(3623090.487)						(3420130.382)	(3248692.740)	(3731675.792)	
Benefit size (BRL 2019)	2335.255	2295.413	2440.160	-144.747					2285.351	2354.365	2147.410	206.955
	(1309.103)	(1304.086)	(1316.469)						(1304.834)	(1348.999)	(1199.909)	
Years of contribution									33.874	34.006	33.612	0.394
									(4.143)	(4.108)	(4.200)	
Was self-employed									0.280	0.153	0.533	-0.380
									(0.449)	(0.360)	(0.499)	
Did not have 85/95 points									0.791	0.795	0.782	0.013
									(0.407)	(0.404)	(0.413)	
Age + Years of contribution									89.943	89.660	90.535	-0.875
									(6.572)	(6.551)	(6.577)	
Observations	2,750,366	1,993,346	757,020		2,719,371	1,961,421	757,950		1,956,948	1,304,360	652,588	

Note: This table summarizes the merge procedures and performs a balance check for the intermediary datasets I employ. First, I merge unique observations from SUIBE PDA and SUIBE LAI using the claiming date, gender and birth date. Second, I merge the resulting merged SUIBE with the RAIS cross-section.

Table D2: Merging SUIBE and RAIS: Logit Models

Dependent Variable:	$\mathbb{1}$(Correct Merge)			
Logit Model:	(1)	(2)	(3)	(4)
Variables				
A. *Geographic variables*				
Same State 0 years	-0.205*** (0.057)	-0.214** (0.103)	-0.214* (0.112)	-0.123 (0.119)
Same State 3 years	-0.007 (0.067)	0.117 (0.103)	0.122 (0.109)	0.155 (0.099)
Same State 5 years	0.157*** (0.057)	0.203** (0.083)	0.218*** (0.082)	0.203*** (0.078)
Same State 8 years	-0.098 (0.071)	-0.121 (0.113)	-0.134 (0.111)	-0.126 (0.105)
Same State 10 years	0.224*** (0.072)	0.217** (0.100)	0.228** (0.100)	0.215** (0.094)
Same State 15 years	1.45*** (0.048)	1.98*** (0.121)	1.97*** (0.123)	1.86*** (0.123)
Same Microregion 0 years	0.305*** (0.045)	0.664*** (0.141)	0.660*** (0.141)	0.676*** (0.129)
Same Microregion 2 years	0.166*** (0.052)	0.239*** (0.064)	0.245*** (0.063)	0.226*** (0.064)
Same Microregion 5 years	0.140*** (0.042)	0.250*** (0.052)	0.244*** (0.052)	0.259*** (0.056)
Same Microregion 8 years	0.173*** (0.050)	0.239*** (0.059)	0.239*** (0.061)	0.222*** (0.058)
Same Microregion 10 years	0.181*** (0.049)	0.314*** (0.051)	0.322*** (0.050)	0.326*** (0.050)
Same Microregion 15 years	1.55*** (0.032)	2.29*** (0.109)	2.27*** (0.110)	2.27*** (0.096)
Same Municipality 0 years	0.450*** (0.037)	0.328*** (0.107)	0.328*** (0.108)	0.395*** (0.100)
Same Municipality 2 years	0.228*** (0.043)	0.214*** (0.044)	0.219*** (0.045)	0.209*** (0.051)
Same Municipality 5 years	0.128*** (0.035)	0.107*** (0.029)	0.105*** (0.030)	0.100*** (0.035)
Same Municipality 8 years	0.047 (0.041)	0.052 (0.038)	0.065* (0.037)	0.067* (0.039)
Same Municipality 10 years	0.100** (0.040)	-0.024 (0.041)	-0.032 (0.040)	-0.015 (0.038)
Same Municipality 15 years	0.793*** (0.025)	0.657*** (0.091)	0.665*** (0.092)	0.706*** (0.097)
B. *Financial variables*				
Same Salary/Benefit decile	0.215*** (0.010)	0.203*** (0.038)	0.198*** (0.038)	0.228*** (0.037)
Same Salary/Benefit quartile	1.11*** (0.008)	1.05*** (0.061)	1.06*** (0.062)	1.06*** (0.057)
C. *Claiming variables*				
Male	0.223*** (0.008)	-0.151*** (0.019)	-0.241*** (0.020)	-0.437*** (0.034)
RAIS ER Claim (same year)	2.37*** (0.026)	2.43*** (0.053)	2.51*** (0.051)	2.23*** (0.030)
RAIS Retirement claim (not ER)	-1.57*** (0.023)	-1.35*** (0.255)	-1.35*** (0.255)	-0.835*** (0.090)
RAIS ER claim	-0.734*** (0.016)	-0.973*** (0.053)	-0.993*** (0.054)	-0.714*** (0.037)
Benefit size	-0.002***	-0.0007***	-0.0007***	-0.0008***
	(1.4×10^{-5})	(0.0002)	(0.0002)	(0.0002)
Benefit size^2	2.63×10^{-7}***	1.12×10^{-7}***	1.15×10^{-7}***	1.35×10^{-7}***
	(2.67×10^{-9})	(3×10^{-8})	(3.19×10^{-8})	(3.29×10^{-8})
Salary	9.46×10^{-6}***	7.87×10^{-5}***	8.05×10^{-5}***	3.51×10^{-5}***
	(1.4×10^{-6})	(1.26×10^{-5})	(1.25×10^{-5})	(1.19×10^{-5})
Salary^2	-2.05×10^{-10}***	-3.67×10^{-9}***	-3.65×10^{-9}***	-3.71×10^{-9}***
	(6.29×10^{-12})	(1.29×10^{-9})	(1.29×10^{-9})	(1.28×10^{-9})
Share of years employed	2.55*** (0.059)	2.93*** (0.104)	2.77*** (0.111)	2.35*** (0.090)
Share of years employed^2	0.125*** (0.048)	-0.411*** (0.094)	-0.308*** (0.084)	0.134 (0.119)
Constant	-4.87*** (0.024)			
Fixed-effects				
Microregion (508)		✓	✓	✓
Schooling (11)		✓	✓	✓
Type of issuance (6)			✓	✓
Job sector (SUIBE) (7)			✓	✓
Affiliation type (6)			✓	✓
Occupation [CBO 4] (587)				✓
Industry [CNAE 3] (220)				✓
Fit statistics				
Observations	1,388,295	1,388,295	1,388,295	1,383,532
Squared Correlation	0.63355	0.70966	0.71179	0.72957
Pseudo R^2	0.59556	0.67014	0.67236	0.69146

Note: This table reports the model coefficients and model fit for the Logit I employ to estimate the predicted probability of a correct merge in the subsample of 370 thousand individuals whose full CPF I observe in the data. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table D3: Balance check for SUIBE-RAIS sample

	Merged SUIBE-RAIS	In sample	Out of sample	Difference
A. ***Demographic and employment-related variables***				
Male	0.631 (0.483)	0.633 (0.482)	0.614 (0.487)	0.019
Birth year	1960.606 (5.232)	1960.888 (5.120)	1958.708 (5.570)	2.181
Completed College	0.187 (0.390)	0.183 (0.386)	0.218 (0.413)	-0.035
Completed High school	0.523 (0.499)	0.532 (0.499)	0.463 (0.499)	0.069
Share of formal employment	0.910 (0.259)	0.972 (0.114)	0.421 (0.474)	0.551
Share of full-time employment	0.971 (0.146)	0.988 (0.075)	0.835 (0.352)	0.152
Prob. employment (10 years bef. claim)	0.961 (0.094)	0.968 (0.061)	0.905 (0.210)	0.063
Was self-employed	0.153 (0.360)	0.130 (0.336)	0.313 (0.464)	-0.184
Bad health proxy	0.252 (0.434)	0.262 (0.439)	0.173 (0.378)	0.089
Average monthly earnings (BRL 2019)	4358.463 (5300.543)	4456.557 (5359.361)	3690.701 (4828.698)	765.856
B. ***Claiming variables***				
Claiming year	2015.102 (2.736)	2015.317 (2.303)	2013.657 (4.445)	1.660
Age at claiming	54.527 (4.837)	54.459 (4.789)	54.987 (5.124)	-0.528
Years of contribution	34.006 (4.108)	34.020 (4.001)	33.910 (4.769)	0.110
Benefit size (BRL 2019)	2354.365 (1348.999)	2385.163 (1345.317)	2147.021 (1355.443)	238.142
Actuarial Replacement rate	0.723 (0.154)	0.719 (0.151)	0.756 (0.171)	-0.037
Did not have 85/95 points	0.795 (0.404)	0.797 (0.402)	0.780 (0.414)	0.017
Judicialized issuance	0.242 (0.429)	0.223 (0.416)	0.373 (0.484)	-0.150
Age + Years of contribution	89.660 (6.551)	89.557 (6.522)	90.407 (6.717)	-0.849
C. ***Regional variables***				
Central-west region	0.038 (0.192)	0.039 (0.193)	0.037 (0.189)	0.002
Northeast region	0.124 (0.330)	0.121 (0.326)	0.150 (0.357)	-0.029
North region	0.020 (0.140)	0.019 (0.137)	0.025 (0.155)	-0.005
Southeast region	0.525 (0.499)	0.535 (0.499)	0.453 (0.498)	0.082
South region	0.293 (0.455)	0.286 (0.452)	0.335 (0.472)	-0.049
State capital	0.298 (0.457)	0.310 (0.463)	0.213 (0.410)	0.097
Urban resident	0.995 (0.069)	0.998 (0.039)	0.973 (0.163)	0.026
Population size in 2010	1715783.629 (3248692.740)	1812279.031 (3328247.676)	1066140.056 (2558662.268)	746138.975
Observations	1,304,360	1,135,670	168,690	

Note: This table reports the balance check for the full merged SUIBE-RAIS, the selected sample from this dataset (described in Section 3 and Appendix Figure D2), and for the observations out of this sample.

E
Robustness Analyses

Table E1: Robustness – Substitution elasticity of claiming with respect to financial incentives (ε^j_{CH})

Robustness	j	-12	-10	-8	-6	-4	-2	*Summary*	
	$\Delta\%CH_j$	0.433	0.644	0.683	0.763	0.925	1.399	$\Delta\bar{C}H = 0.872$	
π_L = -48, F = 5	$\bar{\varepsilon}^j_{CH}$	-0.164	-0.218	-0.185	-0.121	-0.088	-0.073	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.133	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.083
		(0.009)	(0.008)	(0.007)	(0.004)	(0.002)	(0.002)	$\kappa = 0.388$	
	$\Delta\%CH_j$	0.415	0.623	0.662	0.741	0.900	1.368	$\Delta\bar{C}H = 0.848$	
π_L = -42, F = 5	$\bar{\varepsilon}^j_{CH}$	-0.159	-0.213	-0.181	-0.119	-0.086	-0.072	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.130	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.077
		(0.008)	(0.007)	(0.006)	(0.004)	(0.002)	(0.001)	$\kappa = 0.393$	
	$\Delta\%CH_j$	0.427	0.636	0.675	0.753	0.914	1.384	$\Delta\bar{C}H = 0.861$	
π_L = -30, F = 5	$\bar{\varepsilon}^j_{CH}$	-0.162	-0.216	-0.183	-0.120	-0.087	-0.073	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.132	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.113
		(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.390$	
	$\Delta\%CH_j$	0.405	0.612	0.651	0.730	0.890	1.356	$\Delta\bar{C}H = 0.837$	
π_L = -24, F = 5	$\bar{\varepsilon}^j_{CH}$	-0.155	-0.209	-0.178	-0.117	-0.086	-0.072	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.128	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.120
		(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.395$	
	$\Delta\%CH_j$	0.360	0.562	0.602	0.680	0.837	1.293	$\Delta\bar{C}H = 0.784$	
π_L = -18, F = 5	$\bar{\varepsilon}^j_{CH}$	-0.141	-0.196	-0.168	-0.111	-0.082	-0.070	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.120	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.120
		(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.405$	
	$\Delta\%CH_j$	0.399	0.602	0.638	0.715	0.873	1.337	$\Delta\bar{C}H = 0.823$	
π_L = -36, F = 2	$\bar{\varepsilon}^j_{CH}$	-0.154	-0.207	-0.176	-0.115	-0.084	-0.071	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.126	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.095
		(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.398$	
	$\Delta\%CH_j$	0.399	0.601	0.637	0.713	0.871	1.334	$\Delta\bar{C}H = 0.821$	
π_L = -36, F = 3	$\bar{\varepsilon}^j_{CH}$	-0.154	-0.207	-0.175	-0.115	-0.084	-0.071	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.126	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.096
		(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.398$	
	$\Delta\%CH_j$	0.433	0.639	0.674	0.749	0.906	1.371	$\Delta\bar{C}H = 0.857$	
π_L = -36, F = 4	$\bar{\varepsilon}^j_{CH}$	-0.165	-0.218	-0.184	-0.120	-0.087	-0.072	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.132	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.104
		(0.007)	(0.007)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.392$	
	$\Delta\%CH_j$	0.417	0.625	0.665	0.746	0.910	1.385	$\Delta\bar{C}H = 0.855$	
π_L = -36, F = 6	$\bar{\varepsilon}^j_{CH}$	-0.158	-0.212	-0.181	-0.119	-0.087	-0.073	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.130	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.098
		(0.007)	(0.007)	(0.006)	(0.003)	(0.002)	(0.001)	$\kappa = 0.390$	
	$\Delta\%CH_j$	0.417	0.624	0.664	0.744	0.907	1.381	$\Delta\bar{C}H = 0.853$	
π_L = -36, F = 7	$\bar{\varepsilon}^j_{CH}$	-0.159	-0.212	-0.180	-0.119	-0.087	-0.073	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.130	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.098
		(0.008)	(0.007)	(0.006)	(0.003)	(0.002)	(0.001)	$\kappa = 0.390$	
	$\Delta\%CH_j$	0.421	0.626	0.661	0.736	0.892	1.354	$\Delta\bar{C}H = 0.843$	
π_L = -42, F = 4	$\bar{\varepsilon}^j_{CH}$	-0.162	-0.215	-0.181	-0.118	-0.086	-0.072	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.130	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.085
		(0.007)	(0.007)	(0.006)	(0.003)	(0.002)	(0.001)	$\kappa = 0.395$	
	$\Delta\%CH_j$	0.393	0.594	0.630	0.706	0.863	1.325	$\Delta\bar{C}H = 0.813$	
π_L = -30, F = 3	$\bar{\varepsilon}^j_{CH}$	-0.152	-0.205	-0.174	-0.114	-0.084	-0.071	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.125	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.107
		(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.400$	
	$\Delta\%CH_j$	0.417	0.622	0.659	0.736	0.896	1.366	$\Delta\bar{C}H = 0.846$	
π_L = -48, F = 2	$\bar{\varepsilon}^j_{CH}$	-0.159	-0.212	-0.180	-0.118	-0.086	-0.072	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.129	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.088
		(0.008)	(0.008)	(0.006)	(0.004)	(0.002)	(0.002)	$\kappa = 0.393$	
	$\Delta\%CH_j$	0.389	0.595	0.637	0.718	0.880	1.350	$\Delta\bar{C}H = 0.825$	
π_L = -24, F = 6	$\bar{\varepsilon}^j_{CH}$	-0.149	-0.204	-0.174	-0.115	-0.085	-0.072	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.125	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.116
		(0.007)	(0.007)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.395$	
	$\Delta\%CH_j$	0.345	0.549	0.593	0.677	0.840	1.305	$\Delta\bar{C}H = 0.782$	
π_L = -18, F = 7	$\bar{\varepsilon}^j_{CH}$	-0.134	-0.190	-0.164	-0.110	-0.082	-0.070	$\bar{\bar{\varepsilon}}(-12;-1)$ = -0.118	$\bar{\bar{\varepsilon}}(-\pi_L;-1)$ = -0.116
		(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.403$	

Note: This table reports robustness exercises to the substitution elasticity of pension claiming. I consider alternative values of the excluded range π_L and of the polynomial order F.

Table E2: Robustness – Income Elasticity of Labor Supply with respect to pension size ($-\eta_S^k$)

Quarters since claim	Main Analysis	Shorter Window 1	Shorter Window 2	No IPW	No Indiv. FE, with controls
0	0.910	1.969	3.687	1.270*	0.819***
	(0.762)	(4.412)	(11.902)	(0.691)	(0.224)
1	-0.012	-0.033**	-0.032*	-0.034**	0.024**
	(0.013)	(0.013)	(0.018)	(0.014)	(0.011)
2	-0.092***	-0.108***	-0.104***	-0.127***	-0.019
	(0.034)	(0.030)	(0.030)	(0.040)	(0.024)
3	0.041	0.114**	0.216*	0.065	-0.125*
	(0.045)	(0.055)	(0.115)	(0.043)	(0.065)
4	-0.034	-0.006	-0.008	-0.004	-0.176***
	(0.031)	(0.033)	(0.041)	(0.029)	(0.032)
5	-0.045	-0.043	-0.045	-0.015	-0.147***
	(0.029)	(0.034)	(0.035)	(0.029)	(0.037)
6	-0.090***	-0.076**	-0.061	-0.060*	-0.188***
	(0.030)	(0.038)	(0.040)	(0.032)	(0.040)
7	-0.116***	-0.098***	-0.081*	-0.088***	-0.233***
	(0.030)	(0.038)	(0.042)	(0.034)	(0.037)
8	-0.155***	-0.147***	-0.125***	-0.124***	-0.299***
	(0.029)	(0.036)	(0.042)	(0.032)	(0.034)
9	-0.156***	-0.145***	-0.142***	-0.122***	-0.280***
	(0.032)	(0.034)	(0.043)	(0.035)	(0.039)
10	-0.148***	-0.123***	-0.117**	-0.114***	-0.261***
	(0.033)	(0.037)	(0.046)	(0.036)	(0.045)
11	-0.106***	-0.088**	-0.079*	-0.067**	-0.218***
	(0.031)	(0.035)	(0.042)	(0.034)	(0.040)
12	-0.081***	-0.071**	-0.063*	-0.036	-0.205***
	(0.028)	(0.031)	(0.038)	(0.033)	(0.033)
13	-0.088***	-0.073**	-0.066*	-0.055*	-0.189***
	(0.029)	(0.031)	(0.036)	(0.033)	(0.039)
14	-0.094***	-0.080**	-0.073*	-0.070**	-0.189***
	(0.031)	(0.037)	(0.043)	(0.035)	(0.041)
15	-0.079***	-0.069*	-0.067	-0.052	-0.183***
	(0.030)	(0.037)	(0.043)	(0.033)	(0.039)
16	-0.099***	-0.092***	-0.096**	-0.076**	-0.229***
	(0.028)	(0.034)	(0.039)	(0.033)	(0.034)
17	-0.087***	-0.091***	-0.086**	-0.051	-0.193***
	(0.031)	(0.035)	(0.039)	(0.034)	(0.039)
18	-0.131***	-0.139***	-0.136***	-0.094***	-0.241***
	(0.032)	(0.040)	(0.045)	(0.036)	(0.045)
19	-0.220***	-0.224***	-0.200***	-0.193***	-0.366***
	(0.032)	(0.041)	(0.045)	(0.037)	(0.041)
20	-0.270***	-0.272***	-0.285***	-0.248***	-0.442***
	(0.032)	(0.039)	(0.045)	(0.035)	(0.036)
Fit statistics					
No. Individuals	101,733	83,824	69,544	101,753	101,790
Observations	5,312,076	4,374,909	3,629,967	5,312,076	5,312,043

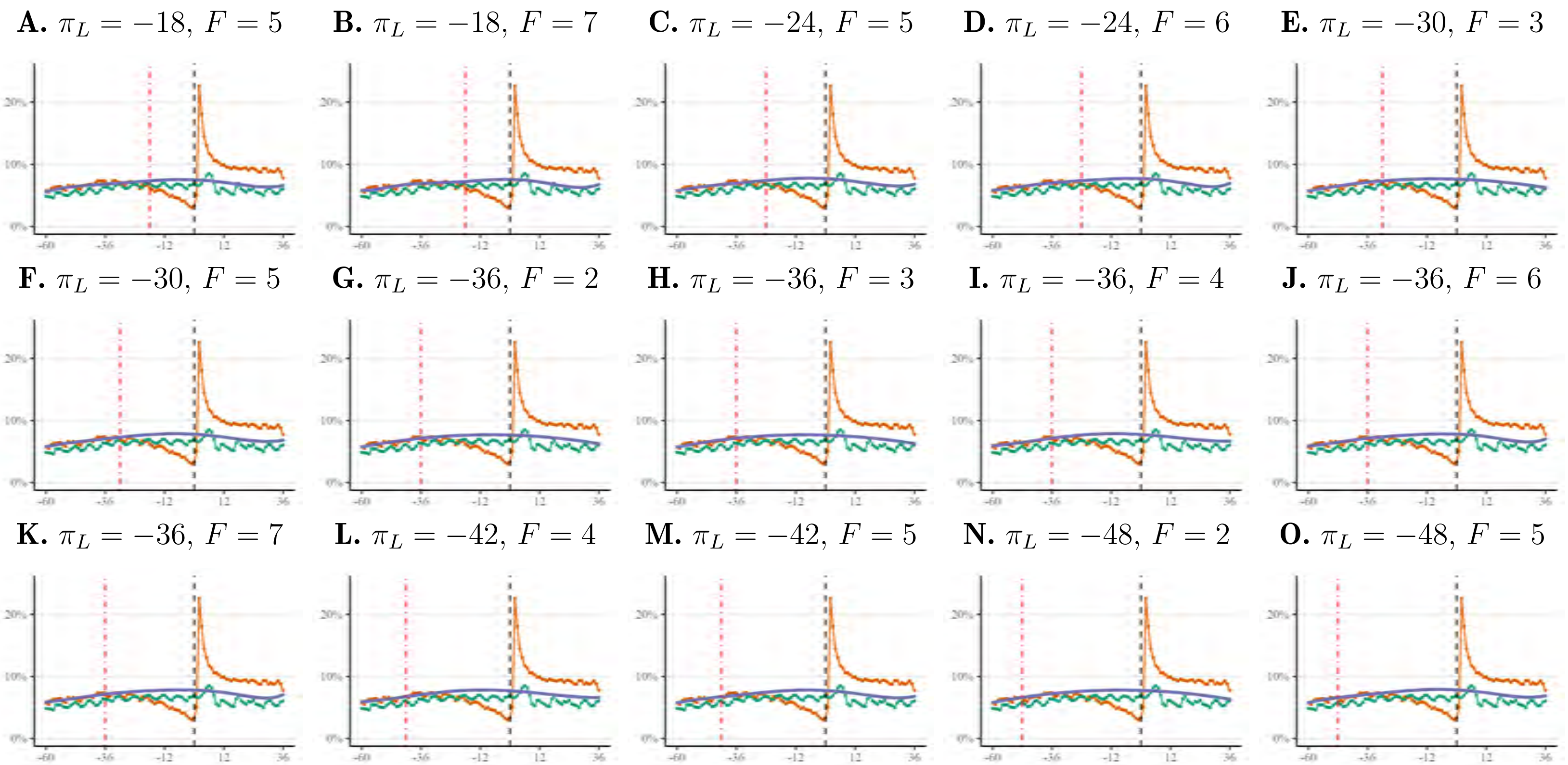
Note: This table reports the results of robustness exercises to the income elasticity of labor supply with respect to benefit size. I consider four robustness exercises described in Section 5. First, I use a shorter window to define the treated and control groups. Second, I consider an even shorter window. Third, I run the analyses without an inverse probability weighting scheme to ensure balance in observable characteristics between control and treated groups. Finally, I consider an specification without individual fixed-effects, but where I control for a rich set of observables. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table E3: Robustness – Fuzzy RD Estimates

Variable	Cutoff	Order	Kernel	Robust		Conventional		Bandwidth	Observations	
				RD est.	SD	RD est.	SD		(Left)	(Right)
Office at hometown	20k	1	Epanechnikov	0.516^{***}	0.069	0.502^{***}	0.058	5592.656	536	341
	20k	1	Uniform	0.515^{***}	0.066	0.506^{***}	0.056	5444.222	514	330
	20k	2	Triangular	0.511^{***}	0.091	0.510^{***}	0.079	7670.599	789	429
	20k	3	Triangular	0.498^{***}	0.102	0.509	0.091^{***}	10277.58	1173	519
	10k	1	Triangular	-0.002	0.036	-0.005	0.029	2761.777	415	407
	30k	1	Triangular	-0.156^{*}	0.088	-0.135^{*}	0.075	6749.416	296	195
Claimed at hometown	20k	1	Epanechnikov	0.424^{***}	0.103	0.455^{***}	0.091	4721.618	437	295
	20k	1	Uniform	0.410^{***}	0.103	0.440^{***}	0.093	3988.232	364	240
	20k	2	Triangular	0.337^{***}	0.141	0.374^{***}	0.126	6631.965	669	391
	20k	3	Triangular	0.368^{***}	0.124	0.395^{***}	0.114	12266.82	1457	598
	10k	1	Triangular	-0.035	4.098	0.240	3.378	3021.329	458	428
	30k	1	Triangular	0.353	0.496	0.327	0.420	6747.310	296	195
Years of contribution	20k	1	Epanechnikov	0.145	0.564	0.155	0.494	6312.711	643	376
	20k	1	Uniform	0.010	0.645	-0.050	0.531	5064.890	470	312
	20k	2	Triangular	0.062	0.720	0.057	0.631	8349.674	874	450
	20k	3	Triangular	0.136	0.751	0.120	0.669	11998.48	1427	591
	10k	1	Triangular	66.728	447.739	41.584	368.441	3129.332	490	443
	30k	1	Triangular	-1.425	3.457	-1.576	2.925	6116.181	277	182
Age + Years of contribution	20k	1	Epanechnikov	-1.052	1.315	-0.973	1.155	4138.207	386	248
	20k	1	Uniform	-0.438	1.285	-0.512	1.080	4417.078	412	269
	20k	2	Triangular	-0.887	1.450	-0.845	1.287	7379.293	759	418
	20k	3	Triangular	-0.663	1.430	-0.664	1.279	11962.81	1425	590
	10k	1	Triangular	-266.032	1156.953	-113.660	950.741	3085.034	478	436
	30k	1	Triangular	-6.007	7.003	-5.206	5.991	6485.844	286	190
Eligible to 85/95	20k	1	Epanechnikov	-0.019	0.101	-0.033	0.089	4116.642	382	248
	20k	1	Uniform	-0.062	0.089	-0.070	0.077	5224.963	486	321
	20k	2	Triangular	-0.008	0.117	-0.022	0.103	6829.924	695	400
	20k	3	Triangular	0.010	0.113	-0.006	0.101	11540.59	1352	578
	10k	1	Triangular	-80.965	1334.091	-31.209	1087.787	3781.405	630	522
	30k	1	Triangular	0.155	0.461	0.155	0.389	6825.491	300	199
Pension deferral (years)	20k	1	Epanechnikov	-0.564	0.426	-0.590	0.370	5562.261	531	338
	20k	1	Uniform	-0.449	0.471	-0.580	0.415	3940.629	365	236
	20k	2	Triangular	0.007	0.530	-0.171	0.473	6692.421	678	392
	20k	3	Triangular	0.224	0.542	-0.003	0.491	10510.89	1209	527
	10k	1	Triangular	-0.652	275.509	-31.160	228.625	2395.549	345	361
	30k	1	Triangular	-1.835	2.434	-1.635	2.073	5655.967	244	177
Actuarial Replacement rate	20k	1	Epanechnikov	-0.036	0.032	-0.035	0.028	4082.492	378	246
	20k	1	Uniform	-0.028	0.027	-0.028	0.024	5451.495	515	330
	20k	2	Triangular	-0.035	0.035	-0.033	0.031	7176.835	732	411
	20k	3	Triangular	-0.026	0.035	-0.026	0.031	11734.23	1377	584
	10k	1	Triangular	-13.453	63.406	-5.099	52.094	3211.192	507	458
	30k	1	Triangular	-0.168	0.192	-0.142	0.163	7176.082	320	206
Actual Replacement rate	20k	1	Epanechnikov	-0.005	0.075	-0.020	0.065	5119.106	474	315
	20k	1	Uniform	0.002	0.075	-0.017	0.064	4874.592	456	304
	20k	2	Triangular	-0.012	0.078	-0.031	0.068	9777.530	1131	496
	20k	3	Triangular	0.005	0.086	-0.012	0.076	12837.30	1566	610
	10k	1	Triangular	-8520.199	190656.288	-217.658	155741.095	3663.107	611	499
	30k	1	Triangular	0.092	0.337	0.069	0.279	6636.621	290	194
Benefit size (BRL 2019)	20k	1	Epanechnikov	-90.982	317.797	-44.881	272.934	4954.842	462	308
	20k	1	Uniform	-46.941	299.939	-74.481	255.193	5176.404	481	320
	20k	2	Triangular	-58.529	318.037	0.050	275.760	11049.878	1277	553
	20k	3	Triangular	-118.716	357.646	-72.706	318.005	12940.30	1591	612
	10k	1	Triangular	-108705.975	667738.502	-21342.615	547050.157	3436.426	562	476
	30k	1	Triangular	-684.006	1454.367	-679.988	1218.361	6292.683	280	187
Last year employed (until 2020)	20k	1	Epanechnikov	-0.032	0.406	0.094	0.352	4579.910	423	284
	20k	1	Uniform	0.084	0.420	0.187	0.356	4314.762	401	260
	20k	2	Triangular	-0.625	0.489	-0.340	0.427	6476.213	666	384
	20k	3	Triangular	-0.469	0.482	-0.220	0.430	10738.07	1232	538
	10k	1	Triangular	27.310	168.664	18.283	138.907	3030.801	463	431
	30k	1	Triangular	1.205	1.894	0.811	1.633	6585.559	289	192
Number of claims	20k	1	Epanechnikov	-17.037	12.464	-10.979	10.287	5194.832	483	320
	20k	1	Uniform	-19.633	13.327	-11.420	10.897	4618.487	426	285
	20k	2	Triangular	-15.645	13.291	-14.315	11.818	7714.807	797	431
	20k	3	Triangular	-12.629	13.163	-13.848	12.046	12156.40	1444	595
	10k	1	Triangular	27024.680	318788.214	4876.858	261648.229	3547.013	586	481
	30k	1	Triangular	105.884	99.381	74.627	87.664	6815.820	300	199

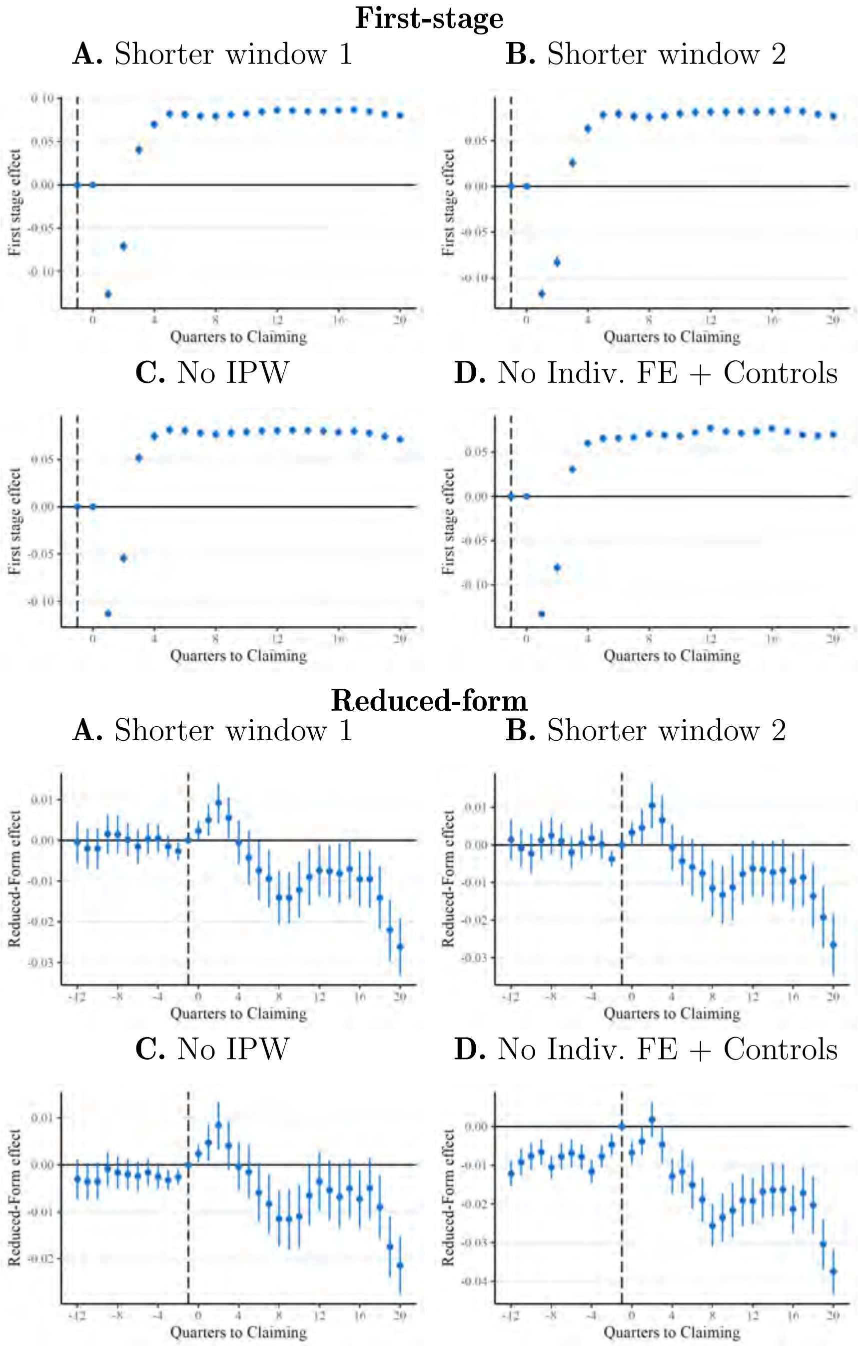
Note: This table presents several robustness exercises to the fuzzy RD estimate reported in Section 7. I consider alternative cutoffs of population-size, alternative polynomial orders and alternative kernels. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Figure E1: Robustness – Difference-in-bunching strategy



Note: This figure presents the robustness exercises to the difference-in-bunching strategy. I consider alternative values of the excluded range π_L and of the polynomial order F to create the counterfactual claiming hazard after the reform.

Figure E2: Robustness – First-stage and Reduced-form effects of the 2015 Reform

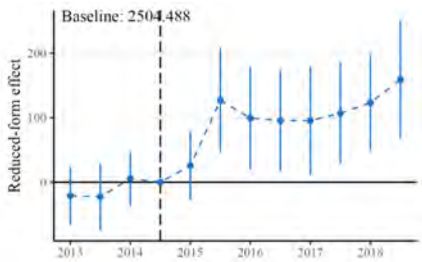


Note: This figure reports the results of robustness exercises to the reduced-form and first-stage effects of the 2015 Reform. I consider four robustness exercises described in Section 5. First, I use a shorter window to define the treated and control groups. Second, I consider an even shorter window. Third, I run the analyses without an inverse probability weighting scheme to ensure balance in observable characteristics between control and treated groups. Finally, I consider an specification without individual fixed-effects, but where I control for a rich set of observables.

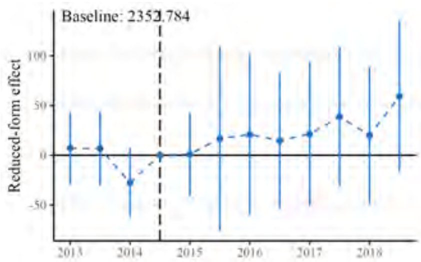
Figure E3: Robustness – Effect of more local knowledge on response to the 2015 Reform

Benefit size

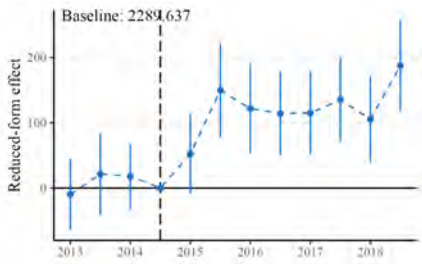
A. Q1 vs Q3



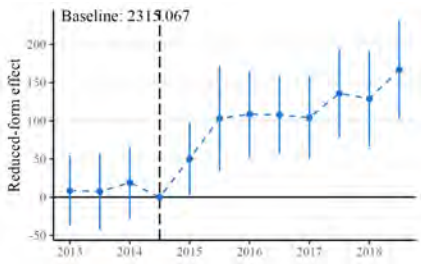
B. Q2 vs Q4



C. Proxy using at least 20 claims

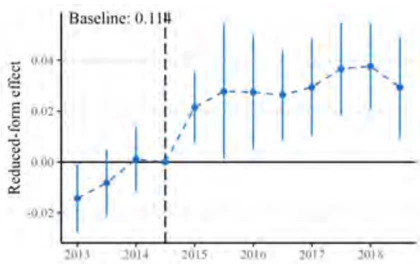


D. Proxy using at least 50 claims

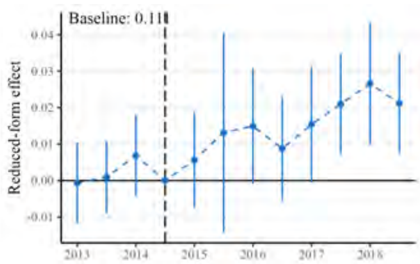


Eligibility to 85/95

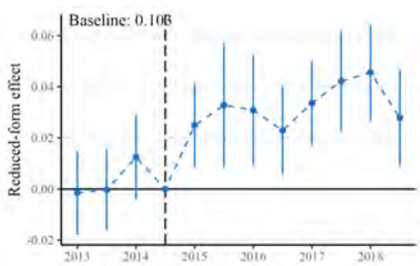
A. Q1 vs Q3



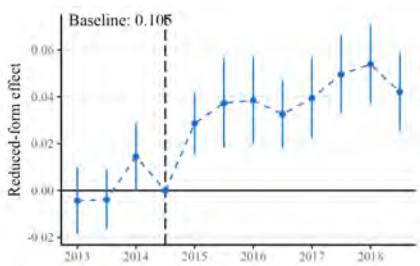
B. Q2 vs Q4



C. Proxy using at least 20 claims



D. Proxy using at least 50 claims



Note: This figure presents robustness exercises to the effect of more local knowledge on the response to the 2015 Reform. I consider four alternative definitions of local knowledge. First, I compare Q1 with Q3, and Q2 with Q4. Second, I consider alternative knowledge proxies where I focus on the 2,413 municipalities which had at least 20 claims of early retirement before 2015, or the 1,435 municipalities with at least 50 claims, instead of 30 claims which I used in the main analysis.

F
Heterogeneity Analyses

Table F1: Heterogeneity – Substitution elasticity of claiming with respect to financial incentives (ε^{j}_{CH})

Heterogeneity	j	-12	-10	-8	-6	-4	-2	*Summary*	*Obs.*
Women	$\Delta\%b_j$	7.852	8.625	9.631	11.145	33.119	56.569	$\bar{\Delta b} = 26.757$	275,548
	$\Delta\%CH_j$	0.670	1.064	1.069	1.218	1.153	1.995	$\Delta\bar{CH} = 1.274$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.127	-0.184	-0.165	-0.163	-0.052	-0.052	$\bar{\bar{\varepsilon}} =$ -0.112	
		(0.006)	(0.006)	(0.005)	(0.005)	(0.002)	(0.001)	$\kappa = 0.328$	
Men	$\Delta\%b_j$	3.961	4.367	4.926	5.909	16.575	29.348	$\bar{\Delta b} = 12.921$	587,325
	$\Delta\%CH_j$	0.302	0.429	0.472	0.516	0.758	1.052	$\Delta\bar{CH} = 0.639$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.136	-0.176	-0.171	-0.156	-0.082	-0.064	$\bar{\bar{\varepsilon}} =$ -0.127	
		(0.007)	(0.007)	(0.006)	(0.005)	(0.002)	(0.001)	$\kappa = 0.441$	
Nonwhite	$\Delta\%b_j$	4.109	4.563	5.408	9.929	16.672	29.877	$\bar{\Delta b} = 14.077$	196,014
	$\Delta\%CH_j$	0.305	0.465	0.535	0.466	0.724	1.087	$\Delta\bar{CH} = 0.630$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.140	-0.192	-0.187	-0.089	-0.082	-0.069	$\bar{\bar{\varepsilon}} =$ -0.120	
		(0.009)	(0.008)	(0.007)	(0.004)	(0.002)	(0.001)	$\kappa = 0.471$	
White	$\Delta\%b_j$	4.375	4.910	6.358	10.374	17.347	31.585	$\bar{\Delta b} = 15.140$	662,778
	$\Delta\%CH_j$	0.474	0.702	0.725	0.878	0.985	1.496	$\Delta\bar{CH} = 0.954$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.170	-0.224	-0.179	-0.133	-0.089	-0.074	$\bar{\bar{\varepsilon}} =$ -0.137	
		(0.007)	(0.007)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.363$	
Low earnings	$\Delta\%b_j$	4.428	4.998	8.235	10.401	17.108	31.346	$\bar{\Delta b} = 15.187$	363,883
	$\Delta\%CH_j$	0.212	0.381	0.429	0.422	0.648	0.915	$\Delta\bar{CH} = 0.544$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.094	-0.150	-0.102	-0.080	-0.074	-0.057	$\bar{\bar{\varepsilon}} =$ -0.091	
		(0.007)	(0.006)	(0.004)	(0.003)	(0.002)	(0.001)	$\kappa = 0.491$	
High earnings	$\Delta\%b_j$	4.255	4.742	5.718	10.207	17.212	31.090	$\bar{\Delta b} = 14.852$	498,990
	$\Delta\%CH_j$	0.628	0.874	0.895	1.082	1.142	1.860	$\Delta\bar{CH} = 1.166$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.217	-0.272	-0.231	-0.156	-0.098	-0.088	$\bar{\bar{\varepsilon}} =$ -0.165	
		(0.009)	(0.009)	(0.007)	(0.004)	(0.003)	(0.002)	$\kappa = 0.322$	
Good health	$\Delta\%b_j$	4.271	4.769	5.862	10.240	17.118	30.977	$\bar{\Delta b} = 14.850$	633,324
	$\Delta\%CH_j$	0.418	0.646	0.679	0.760	0.949	1.427	$\Delta\bar{CH} = 0.883$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.159	-0.220	-0.188	-0.121	-0.090	-0.075	$\bar{\bar{\varepsilon}} =$ -0.134	
		(0.008)	(0.007)	(0.006)	(0.003)	(0.002)	(0.001)	$\kappa = 0.384$	
Bad health	$\Delta\%b_j$	4.441	5.009	7.571	10.424	17.354	31.802	$\bar{\Delta b} = 15.248$	228,496
	$\Delta\%CH_j$	0.460	0.620	0.671	0.744	0.836	1.298	$\Delta\bar{CH} = 0.819$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.173	-0.207	-0.148	-0.120	-0.081	-0.068	$\bar{\bar{\varepsilon}} =$ -0.125	
		(0.007)	(0.007)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.403$	
Blue collar	$\Delta\%b_j$	4.175	4.631	5.322	7.172	17.037	30.638	$\bar{\Delta b} = 13.814$	365,895
	$\Delta\%CH_j$	0.198	0.317	0.330	0.320	0.574	0.793	$\Delta\bar{CH} = 0.460$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.097	-0.140	-0.127	-0.091	-0.069	-0.053	$\bar{\bar{\varepsilon}} =$ -0.092	
		(0.006)	(0.005)	(0.005)	(0.003)	(0.001)	(0.001)	$\kappa = 0.510$	
White collar	$\Delta\%b_j$	4.550	5.438	8.837	10.546	17.296	31.736	$\bar{\Delta b} = 15.825$	488,612
	$\Delta\%CH_j$	0.569	0.839	0.896	1.041	1.097	1.754	$\Delta\bar{CH} = 1.109$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.190	-0.234	-0.154	-0.150	-0.096	-0.084	$\bar{\bar{\varepsilon}} =$ -0.142	
		(0.009)	(0.008)	(0.005)	(0.004)	(0.003)	(0.002)	$\kappa = 0.341$	
Incomplete High school	$\Delta\%b_j$	4.151	4.606	5.330	9.610	16.908	30.310	$\bar{\Delta b} = 14.003$	375,290
	$\Delta\%CH_j$	0.194	0.312	0.353	0.345	0.551	0.793	$\Delta\bar{CH} = 0.481$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.091	-0.132	-0.129	-0.070	-0.063	-0.051	$\bar{\bar{\varepsilon}} =$ -0.089	
		(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)	$\kappa = 0.485$	
Completed High school, no College	$\Delta\%b_j$	4.447	5.039	8.367	10.419	17.394	31.855	$\bar{\Delta b} = 15.305$	312,913
	$\Delta\%CH_j$	0.447	0.659	0.669	0.793	0.962	1.438	0.856	
	$\bar{\varepsilon}^{j}_{CH}$	-0.169	-0.220	-0.134	-0.128	-0.093	-0.076	$\bar{\bar{\varepsilon}} =$ -0.128	
		(0.009)	(0.008)	(0.005)	(0.004)	(0.003)	(0.002)	$\kappa = 0.406$	
Completed College	$\Delta\%b_j$	4.767	7.605	8.992	10.644	17.564	32.398	$\bar{\Delta b} = 16.549$	174,670
	$\Delta\%CH_j$	0.819	1.262	1.312	1.549	1.398	2.531	$\Delta\bar{CH} = 1.616$	
	$\bar{\varepsilon}^{j}_{CH}$	-0.237	-0.228	-0.201	-0.200	-0.110	-0.108	$\bar{\bar{\varepsilon}} =$ -0.177	
		(0.013)	(0.009)	(0.008)	(0.007)	(0.004)	(0.003)	$\kappa = 0.273$	

Note: This table reports heterogeneity analyses of the substitution elasticity of pension claiming. I run the analysis separately by gender (men/women), race (white/nonwhite), earnings (low/high), health (good/bad), occupation type (blue/white collar), and educational attainment (incomplete HS, complete HS and incomplete college, completed college).

Table F2: Heterogeneity – Income Elasticity of Labor Supply with respect to pension size ($-\eta_S^k$)

	Sex		Health		Schooling		
Quarters since claim	Women	Men	Good Health	Bad Health	Incomp. High school	Compl. HS, no College	Completed College
0	1.857	0.164	-0.919	-7.088	2.625	-107.620	0.313
	(1.124)	(1.746)	(2.070)	(124.351)	(4.865)	(1064.423)	(0.738)
1	-0.074***	0.027	0.012	-0.086***	0.033	-0.028	-0.056**
	(0.017)	(0.017)	(0.014)	(0.028)	(0.021)	(0.019)	(0.022)
2	-0.370***	-0.023	-0.026	-0.288***	-0.006	-0.082	-0.473***
	(0.110)	(0.034)	(0.032)	(0.074)	(0.044)	(0.058)	(0.169)
3	0.064	-0.012	-0.025	0.155**	-0.105	0.011	0.141***
	(0.041)	(0.110)	(0.050)	(0.078)	(0.096)	(0.095)	(0.050)
4	0.014	-0.094*	-0.061*	0.018	-0.130**	-0.084	0.107***
	(0.032)	(0.053)	(0.033)	(0.047)	(0.054)	(0.056)	(0.038)
5	-0.009	-0.091*	-0.062*	-0.021	-0.144***	-0.110**	0.111***
	(0.031)	(0.055)	(0.032)	(0.045)	(0.053)	(0.053)	(0.037)
6	-0.067**	-0.123**	-0.098***	-0.092*	-0.191***	-0.146***	0.060
	(0.032)	(0.062)	(0.036)	(0.054)	(0.063)	(0.055)	(0.040)
7	-0.075**	-0.174***	-0.113***	-0.136**	-0.182***	-0.200***	0.037
	(0.033)	(0.063)	(0.038)	(0.055)	(0.063)	(0.053)	(0.041)
8	-0.113***	-0.211***	-0.159***	-0.148***	-0.196***	-0.243***	-0.009
	(0.031)	(0.059)	(0.036)	(0.052)	(0.056)	(0.049)	(0.039)
9	-0.105***	-0.223***	-0.168***	-0.145***	-0.191***	-0.243***	-0.020
	(0.032)	(0.056)	(0.037)	(0.052)	(0.052)	(0.051)	(0.039)
10	-0.104***	-0.208***	-0.159***	-0.146***	-0.168***	-0.260***	-0.002
	(0.033)	(0.058)	(0.038)	(0.053)	(0.054)	(0.053)	(0.039)
11	-0.092***	-0.132**	-0.129***	-0.070	-0.130**	-0.206***	0.017
	(0.033)	(0.057)	(0.036)	(0.053)	(0.052)	(0.047)	(0.039)
12	-0.095***	-0.074	-0.104***	-0.035	-0.115**	-0.163***	0.035
	(0.030)	(0.054)	(0.033)	(0.050)	(0.050)	(0.045)	(0.039)
13	-0.093***	-0.087	-0.112***	-0.035	-0.153***	-0.144***	0.031
	(0.031)	(0.054)	(0.036)	(0.052)	(0.053)	(0.048)	(0.040)
14	-0.106***	-0.086	-0.124***	-0.029	-0.152***	-0.148***	0.013
	(0.031)	(0.057)	(0.040)	(0.054)	(0.051)	(0.055)	(0.043)
15	-0.095***	-0.064	-0.117***	0.008	-0.132***	-0.146***	0.028
	(0.030)	(0.057)	(0.038)	(0.054)	(0.051)	(0.052)	(0.044)
16	-0.108***	-0.089	-0.138***	0.002	-0.172***	-0.147***	0.015
	(0.029)	(0.055)	(0.036)	(0.054)	(0.049)	(0.048)	(0.043)
17	-0.098***	-0.080	-0.129***	0.007	-0.143***	-0.166***	0.044
	(0.032)	(0.055)	(0.038)	(0.054)	(0.049)	(0.051)	(0.044)
18	-0.115***	-0.158***	-0.179***	-0.026	-0.225***	-0.216***	0.046
	(0.034)	(0.059)	(0.039)	(0.059)	(0.054)	(0.054)	(0.045)
19	-0.153***	-0.314***	-0.265***	-0.119*	-0.391***	-0.279***	0.022
	(0.035)	(0.063)	(0.041)	(0.061)	(0.060)	(0.053)	(0.046)
20	-0.175***	-0.410***	-0.312***	-0.170***	-0.514***	-0.310***	0.020
	(0.033)	(0.064)	(0.039)	(0.057)	(0.062)	(0.052)	(0.044)
Fixed-effects							
Indiv.	✓	✓	✓	✓	✓	✓	✓
Quarters to claim	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓
Fit statistics							
No. Individuals	32,872	68,898	75,308	25,935	46,330	35,732	19,680
Observations	1,715,868	3,596,175	3,932,016	1,354,023	2,418,306	1,865,985	1,027,752

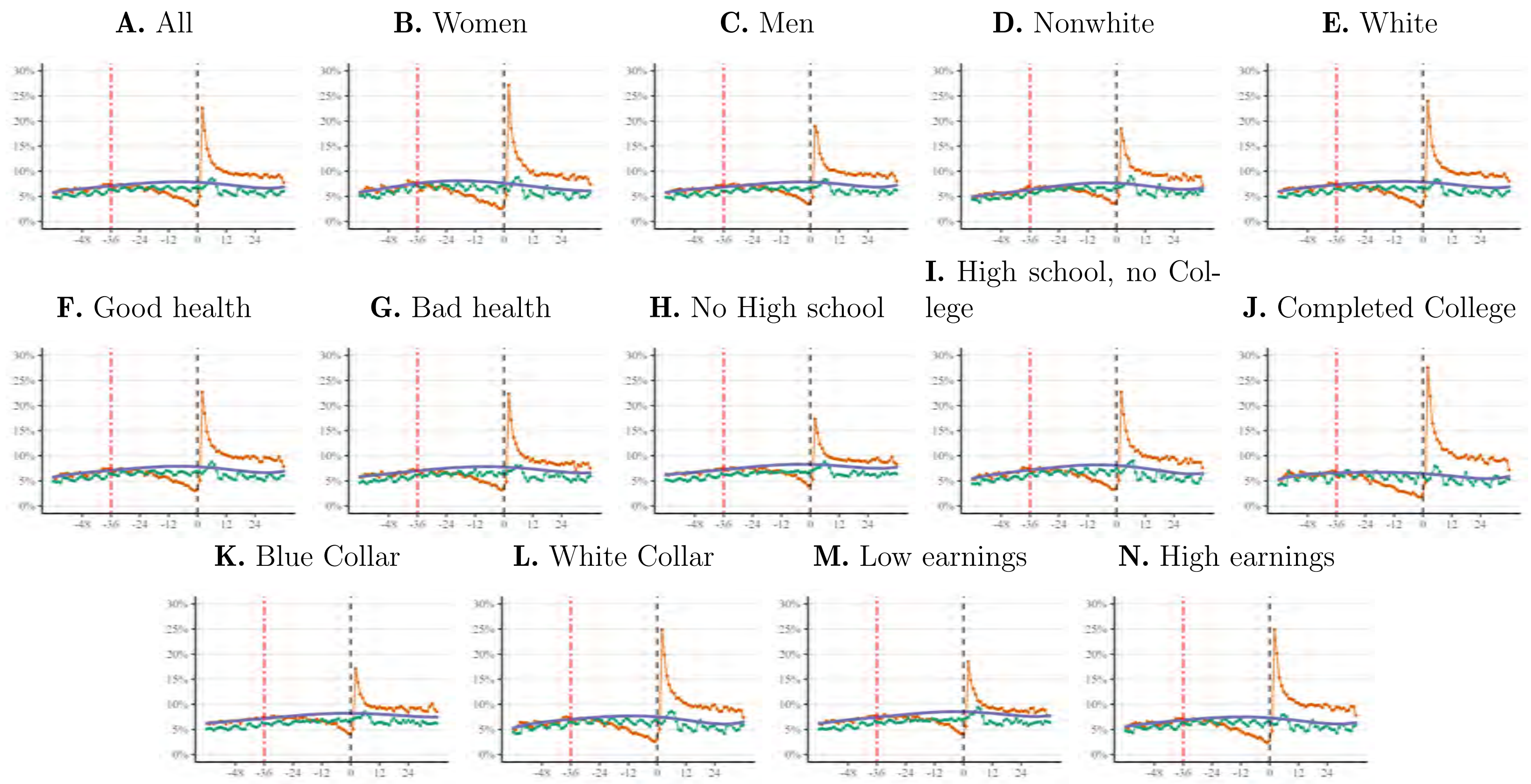
Note: This table reports heterogeneity analyses of the income elasticity of labor supply. I run the analysis separately by gender (men/women), health (good/bad), and educational attainment (incomplete HS, complete HS and incomplete college, completed college). I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Table F3: Heterogeneity – Fuzzy RD Estimates

Category	Variable	Robust		Conventional		Bandwidth	Observations	
		RD est.	SD	RD est.	SD		(Left)	(Right)
Women	Eligible to 85/95	-0.108	0.090	-0.106	0.080	6438.697	631	362
	Claimed at hometown	0.566***	0.072	0.585***	0.058	12377.037	1388	571
	Pension deferral	-0.915	0.444	-0.689*	0.378	7393.313	717	396
	Actuarial Replac. R	-0.020	0.034	-0.019	0.029	4523.172	400	268
	Last year empl.	0.247	0.630	0.265	0.553	6197.032	590	352
	No. claims	-10.687	12.303	-6.349	10.232	9443.241	975	458
	Age + Years contr.	-0.785	1.256	-0.840	1.077	4924.139	440	290
	Actual Replac. R	0.028	0.089	0.013	0.080	6101.312	577	347
	Benefit size	51.455	226.987	56.024	197.585	6801.911	652	379
	Years of contr.	-0.624	0.506	-0.498	0.441	6708.529	640	372
Men	Eligible to 85/95	-0.043	0.083	-0.056	0.071	5976.768	592	369
	Claimed at hometown	0.435***	0.074	0.450***	0.061	8620.890	917	463
	Pension deferral	-0.376	0.331	-0.406	0.292	7321.993	757	422
	Actuarial Replac. R	-0.041	0.031	-0.043	0.027	6618.818	678	400
	Last year empl.	0.488	0.451	0.476	0.386	6098.289	610	374
	No. claims	-9.426	15.980	-3.598	13.252	8537.588	915	462
	Age + Years contr.	-1.149	0.995	-1.305	0.858	6323.863	650	384
	Actual Replac. R	-0.056	0.057	-0.064	0.050	7438.020	775	428
	Benefit size	-80.203	246.410	-92.215	217.999	6877.729	707	409
	Years of contr.	-0.154	0.363	-0.219	0.316	6472.807	670	392
Low Earnings	Eligible to 85/95	-0.093	0.081	-0.087	0.071	7469.661	770	417
	Claimed at hometown	0.411***	0.085	0.440***	0.072	7959.194	825	432
	Pension deferral	-0.534	0.457	-0.561	0.403	4612.891	425	284
	Actuarial Replac. R	-0.040	0.036	-0.032	0.031	4501.527	413	279
	Last year empl.	-0.019	0.570	0.084	0.499	6058.435	603	362
	No. claims	-25.204	25.963	-15.846	22.004	5432.384	511	328
	Age + Years contr.	-1.207	1.536	-0.868	1.310	4969.084	462	306
	Actual Replac. R	0.001	0.075	-0.007	0.066	7011.768	717	399
	Benefit size	-108.155	116.109	-75.554	101.412	4716.112	437	294
	Years of contr.	-0.378	0.881	-0.172	0.745	5416.790	508	328
High Earnings	Eligible to 85/95	-0.035	0.087	-0.044	0.075	7316.175	703	416
	Claimed at hometown	0.484***	0.071	0.497***	0.058	10664.008	1141	532
	Pension deferral	-0.404	0.408	-0.376	0.349	7528.269	731	423
	Actuarial Replac. R	-0.019	0.033	-0.024	0.028	7335.917	703	415
	Last year empl.	0.657	0.445	0.595	0.384	7589.933	739	426
	No. claims	-10.188	7.162	-6.862	5.764	9966.510	1075	505
	Age + Years contr.	-0.987	1.116	-1.088	0.959	7211.310	687	411
	Actual Replac. R	0.027	0.046	0.008	0.040	7095.683	684	408
	Benefit size	-12.220	201.856	-62.748	175.909	7185.468	689	412
	Years of contr.	-0.344	0.472	-0.307	0.406	7349.932	706	416
Incomplete High school	Eligible to 85/95	-0.075	0.098	-0.075	0.083	5440.771	504	325
	Claimed at hometown	0.404***	0.087	0.430***	0.073	6908.578	695	392
	Pension deferral	-0.516	0.472	-0.497	0.404	5483.851	507	329
	Actuarial Replac. R	-0.052	0.037	-0.048	0.031	5138.891	466	312
	Last year empl.	-0.054	0.571	-0.024	0.497	6757.305	677	391
	No. claims	-31.873	23.537	-21.337	19.665	5729.604	545	345
	Age + Years contr.	-1.567	1.430	-1.467	1.211	5499.561	511	330
	Actual Replac. R	-0.012	0.074	-0.017	0.066	6806.046	683	392
	Benefit size	-244.487	209.609	-209.388	184.045	7309.201	745	408
	Years of contr.	-0.250	0.818	-0.124	0.691	5893.882	569	354
Completed High school, no College	Eligible to 85/95	-0.066	0.088	-0.071	0.077	7291.828	725	410
	Claimed at hometown	0.524***	0.068	0.539***	0.056	12262.224	1411	593
	Pension deferral	-0.358	0.365	-0.314	0.317	7502.089	749	418
	Actuarial Replac. R	-0.003	0.030	-0.007	0.026	6612.361	657	386
	Last year empl.	0.753	0.517	0.784*	0.454	6749.021	668	395
	No. claims	-1.808	6.716	-1.847	5.827	9373.614	1001	477
	Age + Years contr.	-0.277	1.310	-0.318	1.135	6499.224	651	381
	Actual Replac. R	-0.014	0.064	-0.028	0.056	7069.387	706	400
	Benefit size	63.540	254.626	56.214	225.197	7678.930	769	423
	Years of contr.	-0.222	0.574	-0.106	0.501	6949.118	693	396
Completed College	Eligible to 85/95	-0.197	0.131	-0.172	0.113	6222.733	428	288
	Claimed at hometown	0.550***	0.097	0.572***	0.080	10107.869	758	391
	Pension deferral	-1.089	0.686	-0.916	0.579	6972.932	481	309
	Actuarial Replac. R	-0.027	0.070	-0.029	0.060	5481.187	360	257
	Last year empl.	-0.800	0.689	-0.748	0.603	5886.714	399	281
	No. claims	-2.738	2.274	-2.482	1.910	7018.619	487	313
	Age + Years contr.	-0.913	2.581	-1.098	2.201	5186.125	338	247
	Actual Replac. R	-0.183	0.099	-0.169	0.087	6463.727	458	297
	Benefit size	-29.826	358.597	-65.306	315.691	6597.754	461	304
	Years of contr.	0.102	1.127	-0.015	0.963	5491.276	363	258

Note: This table reports heterogeneity analyses of the fuzzy RD estimates by gender (men/women), earnings (low/high) and educational attainment (incomplete HS, complete HS and incomplete college, completed college), where I calculate the outcomes at the municipal-level for each group separately. I use $*$ for $p < 0.1$, $**$ for $p < 0.05$ and $***$ for $p < 0.01$.

Figure F1: Heterogeneity – Difference-in-bunching strategy



Note: This figure presents heterogeneity analyses of the difference-in-bunching strategy to create the counterfactual claiming hazard. I run the analysis separately by gender (men/women), race (white/nonwhite), earnings (low/high), health (good/bad), occupation type (blue/white collar), and educational attainment (incomplete HS, complete HS and incomplete college, completed college).

G
Implementation of Welfare Analysis

The MVPF relies on a credible estimation of the net cost of the 2015 pension reform, as well as the average willingness-to-pay of the targeted population. The reform generated incentives for workers to delay their claiming decision until a threshold of age and years of contribution was achieved. More specifically, after the reform the replacement rate of retirement benefits jumped discontinuously to 100% of the average salary, conditional on the worker claiming her pension once the sum of these variables was greater or equal to 85 for women and 95 for men.

The net cost of the pension reform is composed of a mechanical cost and a behavioral cost. The mechanical cost MC is driven by the negative effect on the government budget constraint as workers who claim past the threshold are entitled to a larger pension for the rest of their lives. The behavioral cost BC is composed of four effects. First, there is a positive effect on government net-revenue stemming from the delay in social security payments for those who would have claimed their pensions sooner absent the reform. Second, since their claiming is delayed, their labor market exit decision is also delayed, such that there is an increase in overall income and payroll tax collection. Third, the income effect of a higher pension implies a higher probability of retiring sooner, which reduces income and payroll tax collection. Fourth, the probability of claiming just past the 85/95 is higher due to an income effect. Absent the reform, some workers might have deferred even longer than the required 85/95 points to qualify for the pension increase. After the reform, these individuals are more likely to claim sooner. Therefore, the net cost of the reform depends on four behavioral responses, which are governed by the substitution elasticity of pension claiming $\{\varepsilon_{CH}^{t-\bar{t}}\}_t$, the income elasticity of labor market exit $\{\eta_S^{t-\kappa}\}_t$ and the income elasticity of claiming η_D. In Sections 4 and 5, I have estimated $\{\varepsilon_{CH}^{t-\bar{t}}\}_t$ and $\{\eta_S^{t-\kappa}\}_t$. For the income elasticity of pension claiming, I rely on a result from Ye (2022) and consider $\hat{\eta}_D = 0.047$.

In the following, I describe the procedure to calculate the net cost TC and the mechanical cost MC of the 2015 Reform. I estimate TC and MC at the individual-level, and then aggregate these values using a 3% (annual) real interest rate. The sample of interest are the 156,196 individuals from the main sample who claimed their pensions after June 17th 2015 and had 85/95 points at claiming, such that their pensions were increased due to the 85/95 rule.

G.1 Net cost

For each individual i in the sample, I observe their labor market outcomes conditional on being employed in the formal sector. $empl_{iq}$ is a dummy equal to one if i is employed in quarter q, w_{iq} is the observed salary i received in period q, $claimed_{iq}$ is a dummy equal to 1 if i has claimed her pension by period q, and $b_i(j)$ is the benefit size if worker i claimed her pension in period j relative to the 85/95 threshold. Thus, b_i and b_i^c represent i's actual and counterfactual benefit sizes, respectively.

The panel is structured on the quarter-year-individual level. For each individual i, I observe the calendar year-quarter q, the age of the worker in this quarter $a(q)$, her distance in quarters to the 85/95 threshold $p(q)$, the distance to the observed claiming period $d(q)$, and the time since eligibility to claim an early retirement pension $t(q)$.

I compute the benefit size $b_i(p(q))$ worker i would be eligible to claim in quarter q. This allows me to calculate the impact of pension payments in counterfactual scenarios. Denote by $b_i^c(0)$ and $b_i(0)$ the benefit size that worker i is eligible to claim upon reaching 85/95 points both before and after the reform. Therefore, the percentage change in financial incentives of claiming $p(q)$ quarters away from the threshold is given by:

$$\Delta\% b_i(p(q)) = \begin{cases} \frac{b_i(0)-b_i^c(0)}{b_i^c(0)-b_i(p(q))}, & \text{if } p(q) < 0 \\ \frac{b_i(0)-b_i(p(q))}{b_i(p(q))}, & \text{if } p(q) \geq 0 \end{cases}$$

while the benefit increase due to the 85/95 rule is given by $\frac{b_i(0)-b_i^c(0)}{b_i^c(0)}$.

Denote by T_q the observed income and payroll tax collection for each quarter q and T_q^c the counterfactual collection had the reform not occurred. In addition, B_q represents the total social security benefits payments net of income tax, while B_q^c is the corresponding net payments in the counterfactual scenario where the 2015 Reform did not occur. I define these aggregate variables as the following: $T_q = \sum_i empl_{iq} \times w_{iq}\tau$, $T_q^c = \sum_i empl_{iq}^c \times w_{iq}\tau$, $B_q = claimed_{iq} \times b_i(1-\tau)$. and $B_q^c = claimed_{iq}^c \times b_i^c(1-\tau)$. Therefore, the total cost of the reform in real terms from $\bar{q}$ is given by:

$$TC = -\sum_q \frac{1}{R^{q-\bar{q}}}\Big[(T_q - B_q) - (T^c_q - B^c_q)\Big]$$
$$= -\sum_q \frac{1}{R^{q-\bar{q}}}\sum_i \Big\{\Big[empl_{iq} \times w_{iq}\tau - claimed_{iq} \times b_i(1-\tau)\Big]$$
$$- \Big[empl^c_{iq} \times w_{iq}\tau - claimed^c_{iq} \times b^c_i(1-\tau)\Big]\Big\}$$

Meanwhile, the mechanical cost of the 2015 Reform is calculated as the change in benefit payments keeping individual behavior constant:

$$MC = \sum_q \frac{1}{R^{q-\bar{q}}}\sum_i claimed^c_{iq} \times \Big[b_i - b^c_i\Big](1-\tau)$$

To quantify the impact of the 2015 reform on government revenue, I leverage the estimated elasticities of pension claiming and retirement (along with the estimated financial incentives of deferral and the benefit increase at 85/95 points) to create counterfactual distributions of pension claiming and retirement. A conceptual challenge with this strategy is that these elasticities are of extensive-margin decisions, such that quantifying the effect of the reform on claiming and retirement at the individual-level is not straightforward. This would require observing the underlying probabilities that i is working and claiming at a given period. If this were the case, then I could simply compute the effect of the reform for each individual by calculating the effect on claiming and retirement, given i's financial incentive to delay claiming to 85/95 and her benefit increase. To address this issue, I estimate these underlying probabilities by extracting fixed-effects estimates from the following models:

$$claimed_{iq} = \theta^{claim}_i + \alpha_{p(q)} + \beta^{claim}_{a(q)} + \varepsilon^1_{iq} \tag{G-1}$$

$$empl_{iq} = \theta^{empl}_i + \gamma_{d(q)} + \beta^{empl}_{a(q)} + \varepsilon^2_{iq} \tag{G-2}$$

Where θ^{claim}_i and θ^{empl}_i are individual fixed-effects, $\alpha_{p(q)}$ and $\gamma_{d(q)}$ are distance to the 85/95 cutoff and relative to the claiming period fixed-effects, respectively, and $\beta^{claim}_{a(q)}$ and $\beta^{empl}_{a(q)}$ are age fixed-effects. I run these models separately for men and women. The R-squared statistics associated with the models where claiming is the dependent variable are 0.918 and 0.911 for men and women, respectively. When formal employment is the dependent variable, these statistics are 0.500 and 0.474.

The empirical probabilities of claiming and employment of each individual at each period are calculated as $P^{claim}_{iq} \equiv \hat{\theta}^{claim}_i + \hat{\alpha}_{p(q)} + \hat{\beta}^{claim}_{a(q)}$ and $P^{empl}_{iq} \equiv \hat{\theta}^{empl}_i + \hat{\gamma}_{d(q)} + \hat{\beta}^{empl}_{a(q)}$. I assume that claiming and employment for each individual-period pair follow a Bernoulli distribution, with parameters given by P_{ip}^{claim} and P_{id}^{empl}, such that:

$$claimed_{iq} \sim \text{Bern}(P_{iq}^{claim}) \tag{G-3}$$

$$empl_{iq} \sim \text{Bern}(P_{iq}^{empl}) \tag{G-4}$$

Note that I am drawing from a Bernoulli distribution to generate a claiming sequence. Ideally, this sequence would consist entirely of 0s followed by 1s, as would be observed in the actual claiming distribution. As this is not guaranteed even if the probability of claiming is strictly increasing, I assume that the first occurrence of claiming is valid only when there are three consecutive periods where 1 is the sampled value. Hence, I assume that all following observations will be 1 as well.

Therefore, I estimate the distributions of claiming and employment by running this procedure several times and calculating the average and standard deviation of $claimed_{iq}$ and $empl_{iq}$ for each period q. I construct a 95% confidence interval for both distributions and compare it to the actual distribution in Appendix Figure G2. Reassuringly, the estimated distribution is close to the actual distribution for both variables.

To correctly account for the whole net cost of the reform, we should be able to estimate the fiscal impact in periods that go far beyond our data. I assume that men live until they are 73.1 years old and women until 80.1 years old (which are the IBGE averages for 2019) and create a balanced panel from 40 quarters prior to claiming to the quarter when they reach this age. This raises the challenge of projecting the wage profile of these workers beyond 2020. Additionally, the procedure of estimating the probability of employment at each period and sampling a Bernoulli random variable can also lead to an employment distribution in which a worker is assumed to have worked at a given year (before 2020) when, in fact, she was not on the labor market. We should also be able to estimate what earnings she would have received at that given year if she had worked, based on her prior earnings. Next, I discuss the projection procedure that is employed to address these challenges.

G.1.1 Projection procedure

Let q_F^i and q_L^i refer to the first and last quarters that worker i is observed in RAIS (2003-2020). To complete the missing observations of wages, I employ the following strategy:

$$w_{iq} = \begin{cases} w_{iq}, & \text{if not missing} \\ w_{i,q_F^i}, & \text{if missing and } q < q_F^i \\ \text{spline } w_{iq}, & \text{if missing and } q_F^i < q < q_L^i \\ w_{i,q_L^i} \times f_{a(q)}, & \text{if missing and } q > q_L^i \end{cases}$$

where spline w_{iq} indicates that I run a cubic spline using the adjacent non-missing observations of salary for worker i. To account for the possibility that the wage profile for a given worker is decreasing with age, I multiply the projected future observations of wage and multiply the last observed salary by an adjustment factor $f_{a(q)}$. I define the adjustment factor as the component of salaries which is unexplained by observed and unobserved individual characteristics and by quarter-year controls. I estimate the adjustment factor with the following regression, where I add individual and quarter-year fixed-effects using the SUIBE-RAIS full sample:

$$\log w_{iaq} = \theta_i + \alpha_q + \epsilon_{iaq} \tag{G-5}$$

Then, I calculate the salary adjustment factor as the average of residuals for each age, $f_a \equiv \frac{1}{N_a} \sum_i \hat{\epsilon}_{iaq}$.

G.1.2
Counterfactual distributions

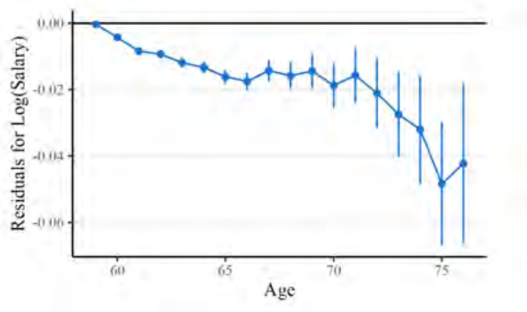
Finally, I estimate the counterfactual distributions of claiming and employment by subtracting the effect of financial incentives generated by the reform from their respective probabilities. Before the 85/95 threshold is achieved, the claiming decision is impacted by the substitution effect governed by the substitution elasticity of pension claiming. After the worker has already qualified for the 85/95 rule, her probability of claiming is impacted by an income effect, which is governed by the income elasticity of claiming. The counterfactual claiming distribution is:

$$claim_{iq}^c \sim \text{Bern}\Big(\hat{\theta}_i^{claim} + \hat{\alpha}_{p(q)} + \hat{\beta}_{a(q)}^{claim} - \Delta\% b_i(q) \times \Big[\mathbb{1}(p(q) < 0) \cdot \hat{\varepsilon}_{CH}^{p(q)} + \mathbb{1}(p(q) \geq 0) \cdot \hat{\eta}_D\Big]\Big)$$

where I use the non-structural substitution elasticity of pension claiming $\varepsilon_{CH}^{p(q)} \equiv \Delta\% CH_{p(q)} / \Delta\% b_{p(q)}$.

Likewise, the employment distribution is affected by the increase in pension size at the 85/95 threshold, given by $\frac{b_i - b_i^c}{b_i^c}$. This behavior is governed by the income elasticity of labor market exit. Hence, the counterfactual

Figure G1: Average log salary residualized by individual and year fixed-effects (f_a)



Note: This figure presents the salary adjustment factor, which I define as the average for each age of the log salary (conditional on employment) residualized by individual and year fixed-effects. I include 95% confidence intervals for each mean.

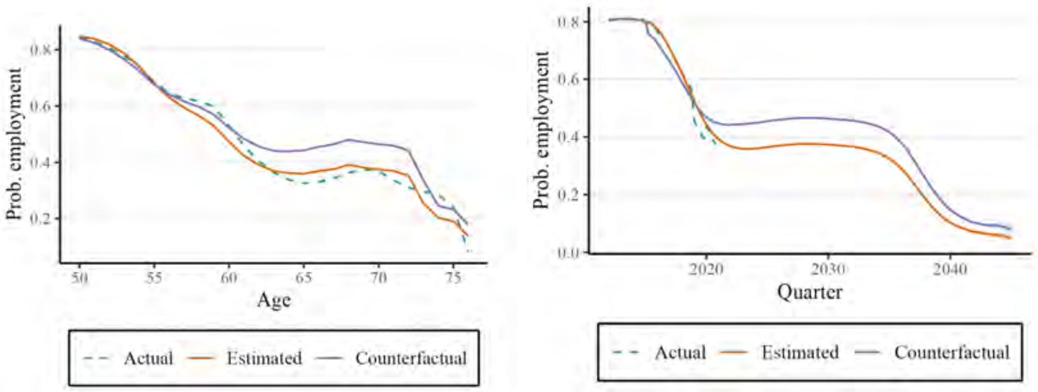
employment distribution is:

$$empl^c_{iq} \sim \text{Bern}\Big(\hat{\theta}^{empl}_i + \hat{\gamma}_{d^c(q)} + \hat{\beta}^{empl}_{a(q)} - \frac{b_i - b^c_i}{b^c_i} \times \hat{\eta}^{d^c(q)}_S\Big)$$

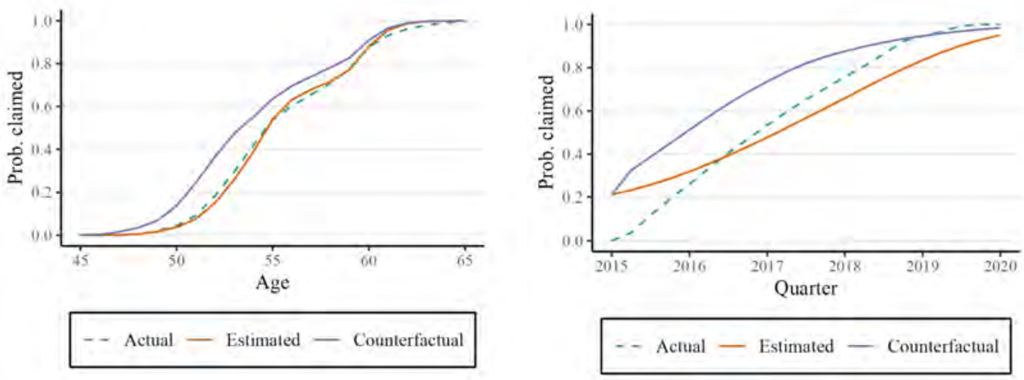
where I recalculate the distance to claiming fixed effects $\hat{\gamma}_{d^c(q)}$ based on the counterfactual claiming distribution derived above.

Figure G2: Creating the counterfactual of the reform: Work and Claiming distributions

Employment distribution



Claiming distribution



Note: This figure reports the results of the counterfactual and estimated claiming and employment distributions, compared to the actual distributions. For each age (left) or quarter-year (right), the figure plots the share of individuals who are working (top) or have already claimed a pension (bottom). The estimated and counterfactual distributions are created using the procedure described in Appendix G.