Unions, Salaries, and the Market for Teachers: Evidence from Wisconsin*

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Abstract

A careful study of teachers' labor demand and supply, while extremely relevant for policy, is challenging due to a lack of variation in pay, as teacher salaries are usually set using steps-and-lanes schedules based entirely on seniority and academic credentials. This paper exploits the passage of Act 10 in Wisconsin in 2011, which changed the scope of collective bargaining on teacher salaries, to study the effects of changes in pay on teachers' labor market, and on the composition of the teaching workforce. As a result of this law some districts started to individually negotiate salaries with each teacher, whereas other districts continued setting salaries using seniority-based schedules. I first document an increase in salary dispersion in individual-salaries districts, and show that it is correlated with teacher value-added. Teachers responded to changes in pay by sorting across districts or by exiting: I find a 34 percent increase in the quality of teachers moving from salary-schedule to individual-salary districts, and a 17 percent decrease in the quality of teachers exiting individual-salary districts. Building from this reduced-form evidence, I estimate the parameters of teachers' labor supply and demand using a two-sided choice model. Simulating the model on different salary schemes shows that an increase in the quality component of salaries in one district is associated with an improvement in average quality of the teaching workforce, driven by both in-movements of higher-quality teachers and out-movements and exits of lower-quality teachers. An increase in all districts is, however, associated with a smaller improvement, entirely attributable to exits of lower-quality teachers.

JEL codes: I20, J31, J45, J51, J61, J63

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1 Introduction

Suppose a school administrator is trying to decide whether she could raise achievement by paying teachers more across the board, paying them based on merit, or raising pay of teachers with unusual skills (advanced math, science). She needs to understand teacher labor supply. That is, she needs to know whether, with higher pay, she will be able to attract teachers who are more sought after or who have to travel a greater distance. Consider a teacher trying to decide whether to make extra effort or learn better pedagogical skills in order to raise her value-added (her causal effect on students' achievement). She needs to understand schools' labor demand. Will they value her improved value-added sufficiently to justify the extra effort or investment in skills?

The above examples are simple but, in fact, an accurate understanding of teacher supply and demand is necessary for most policy decisions in education: school finance equalization, school accountability, charter schools, teacher training, and many others. Most notably, understanding the functioning of teachers' labor market is useful to address the problem of retention, turnover, and shortage of teachers, an issue in virtually all US states (Hanushek et al., 2004; Ingersoll and May, 2012). Teacher turnover is expensive: the cost of a teacher departing from a school has been estimated to be around \$15,000 in 2000, which translates into a \$2.25 billion cost for the US as a whole. Turnover affects student achievement, both directly, by disrupting instruction (Boyd et al., 2008; Ronfeldt et al., 2013), and indirectly, by affecting the composition of the teaching workforce (Adnot et al., 2016). As teachers are the most important input in the production of student achievement (Rockoff, 2004) and have long-lasting effects on students' outcomes (Chetty et al., 2014b), the consequences of changes in the composition of the teaching workforce can potentially be very important.

Despite its relevance, a careful study of teachers' supply and demand has been challenging to conduct, due to a dearth in useful variation in pay practices among public school districts, which dominate US elementary and secondary education. The vast majority of districts, and all unionized ones, have paid teachers according to similar "lock-step" schedules. Under this regime all teachers with the same degree (i.e. a Bachelor or a Master) and years of seniority were paid exactly the same amount, regardless of their value-added, their special skills, or the demand for their labor (Podgursky, 2006). These schedules are often very similar across all districts within a state, owing to "pattern bargaining" facilitated by the state teachers' union. With pay set in this rigid way, identifying labor supply and demand is very challenging. Existing evidence has relied on bonus programs given in addition to regular pay (Hanushek et al., 2004; Clotfelter et al., 2008; Dee and Wyckoff, 2015) or on the limited existing cross-sectional variation in salaries (see Stinebrickner, 2001; Boyd et al., 2013, as an example).

This paper attempts to produce well-identified estimates of teacher supply and demand by analyzing Act 10, a 2011 law that allowed school districts in Wisconsin to negotiate pay with individual teachers, using any criteria the two sides deemed useful (under Act 10, there could still be collective bargaining on a minimum salary but not on any other aspect of teacher pay). Previous to the Act, Wisconsin had been a state with very strict adherence to lock-step schedules. Nevertheless, in the aftermath of Act 10, considerable variation in pay arose among teachers who would previously have been paid exactly the same amount. Notably, pay rose more for teachers with higher value-added and vice-versa. This is an important finding in itself, because it indicates that school districts care about and value, among other things, teachers' value-added.

After Act 10, some districts took immediate advantage of their new-found discretion and moved quickly to set pay on an individual basis, paying teachers with higher value-added more. Other districts instead maintained their pre-Act 10 salary schedules. A simple Roy model predicts that high value-added teachers would flow from salary-schedule to individual-salary districts. It also predicts that low value-added teachers would flow in the opposite direction or exit teaching altogether. Because of these predicted flows, the Roy model also predicts that teacher turnover would rise generally and that achievement would rise in individual-salary relative to salary-schedule districts.

I demonstrate that all of the Roy Model's predictions are borne out using a difference-in-differences framework, which compares individual-salary to salary-schedule districts before versus after Act 10. For instance, I find that average quality of movers from individual-salary to salary-schedule districts rose by 34 percent, while average quality of exiters from salary-schedule districts fell by 17 percent. Interestingly, I find that math achievement rose in individual-salary districts relative to salary-schedule districts, and that the rise was too large to be attributed purely to the inflow of teachers with high pre-existing value-added and the exit of teachers with low pre-existing value-added. This suggests that individual-salary districts' pay for value-added caused either (i) its incumbent teachers to improve their effort and skills to raise their value-added and/or (ii) a rise in value-added among newly-minted teachers who applied to teach there.[1]

The difference-in-differences analysis generates a few key findings, which confirm the predictions of a simple Roy model. Districts did respond to Act 10 and use their newly-acquired discretion. In addition, individual-salary districts appear to care about measured teachers' value-added (of course, this does not rule out the possibility that districts care about teacher attributes that we do not measure). More generally, teachers' labor market appears to function like other labor markets. For

[1]The lack of past test scores data for new teachers prevents me from computing their value-added. The implications of a change in the supply of new teachers are discussed in the next sections.

instance, higher pay does attract teachers. This result was not obvious *ex-ante*, as other works have suggested that teachers are not motivated by pay but by other job characteristics (Hanushek et al., 2004).

These findings motivate me to estimate a full-blown model of teachers' supply and demand. On the supply side of the model, teachers receive job offers and choose among them based on pay and other job characteristics, such as location and the composition of the student body. On the demand side, districts make offers to prospective teachers based on their value-added, credentials, and seniority. The supply side of the model is identified by the differences in pay that emerged in the aftermath of Act 10, which arose not only between salary-schedule and individual-salary districts, but also within individual-salary districts. As a concrete example, consider a high value-added teacher whose incumbent district continues to use its salary schedule but whom, in the aftermath of Act 10, is offered a job with higher pay but a longer commute in an individual-salary district. Her choices reveal the parameters of the supply function. The identification of the demand side of the model is more subtle, and relies on differences in districts' budget and capacity constraints. As an example, consider two identical districts, A and B. Suppose that, in the aftermath of Act 10, both districts make pay more dependent on value-added to the same extent, and have exactly one low value-added teacher exit as a consequence. If district A's exiting teacher has 30 years of experience but district B's teacher has only 1, then district A may have three times as much money "freed up" when the teacher exits (because pre-Act 10 salary schedules had a steep pay gradient in seniority). How it spends its extra funds reveals how teacher attributes are valued, i.e. allows to identify the parameters of the demand function.

The formal model allows me to go beyond the reduced-form evidence. In particular it allows me to separately identify supply and demand forces at play in shaping the teacher-district matches observed in equilibrium. Estimating teachers' labor supply and demand is useful for two reasons. First, estimates can be used to compute the monetary value of non-wage job characteristics valued by the teachers. This allows, for example, to quantify how much more a teacher would have to be paid to teach in a district that is further away, or that has a higher share of low-income students. Similarly, this exercise is helpful to quantify how much more a district would have to pay in order to attract a high value-added teacher. Second, estimates of the model can be used to study the effects of counterfactual policies, such as an increase in the salary/quality correlation in one district (proxy for "merit" or "quality" pay), or a more "universal policy" in which in this change affects all districts, on the composition of the workforce in each district and in the state as a whole. Last but not least, the model allows me to exploit all of the variation in pay regimes induced by Act 10. In fact, districts did not split neatly into salary-schedule and individual-salary groups. Some individual-salary districts used their post-Act 10 freedom to set salaries that were highly individualized. Other individual-salary districts made only modest adjustments in pay relative to their old salary schedules. Thus, the model makes use of much more variation than the reduced-form analysis.

Estimates of the parameters of the model confirm and extend my reduced-form findings. Teachers value higher salaries, face substantial moving costs, prefer urban districts over suburban and rural districts, as well as districts located closer to them. The salary elasticity of moving to a district is, however, rather small compared with the elasticity of distance. These elasticities imply, for example, that a 2-miles longer distance is offset by a large 16 percent increase in salaries. On the demand side, districts value teachers with higher value-added, higher seniority, and with a Master: for example, a teacher with a 10-percent of a standard deviation higher value-added is equiparable to a teacher with 4 extra years of experience. This exercise is useful to examine the short-run effects of some districts moving to individual pay, as it identifies the short-run elasticities of moving (sorting) among districts and the elasticities of exit from teaching.

I use these estimates to understand how the patterns of selection and retention of teachers would change under a set of counterfactual pay schemes. I specifically focus on two changes in the salary scheme. The first is a short-term analysis of one district increasing its quality-related component of salaries. The second is a longer-term analysis of the increase in quality pay in all districts.

Results from the first counterfactual exercise show that an increase in merit pay in one district is associated with an increase of average value-added of the teaching workforce. This increase is driven by an inflow of higher value-added teachers from other districts and an outflow of lower value-added teachers, who either move to other districts or exit.

The second counterfactual exercise is more challenging to study, due to the general equilibrium effects of a universal policy. A change in salary schemes in all districts could, in the long run, affect the supply of new teachers. Changes in the average quality of new teachers are not yet observable in the data, and a thorough analysis of these patterns represents a promising avenue for furture research. These changes are, in fact, likely to take place over a longer time horizon than the three post-Act 10 years included in my analysis. For the sake of my calculations I abstract from these changes and focus on the compositional change driven by movements of teachers across districts and from exit. Results from these calculations show that an increase in merit pay in all districts is associated with a smaller increase of average value-added of the teaching workforce. This happens because, when districts reward seniority at the same rate, teachers have much less incentives to move across districts, and the entire observed compositional change is driven by exit of low-quality teachers. This exercise is useful to understand what would happen to Wisconsin districts if *all* districts change their salary schemes towards individual salaries and, to various extents, start linking salaries to teacher quality - a scenario that is likely to arise as districts start poaching teachers from each other. In addition, it shows that the observed improvement in the composition of the workforce and the achievement gains experienced by individual-salary districts might be short-lived, and that the long-term effects of an overall change in salaries might be smaller. Again, evidence from this counterfactual abstracts from changes in the supply of new teachers, and therefore does not encompass the full long-run consequences of an increase in quality pay. It is, however, useful to shed light onthe long-run consequences that would flow only through sorting and exit.

This paper makes four substantial contributions. First, it exploits newly-available adequate variation in teacher salaries to credibly estimate the supply and demand of teachers. This allows to answer long-standing, general questions on the functioning of this labor market, and to better design compensation policies aimed at attracting and retaining higher-quality teachers.[2] Second, it can be seen as as an exploration, in the personnel economics tradition (Lazear, 2000a,b; Bandiera et al., 2005; Abramitzky, 2009), of how pay affects selection and incentives of a particularly important class of workers. In this perspective, the closest paper is Dee and Wyckoff (2015), who study the effect of the IMPACT program in DC, which provided high-powered incentives and dismissal threats to teachers.[3] In addition, this paper studies a substantial change of the entire salary scheme as opposed to smaller bonus programs complementing regular salaries - the only programs available until Act 10 was passed - which have been the focus of other US-based research. Third, to my knowledge this paper provides the first evaluation of Act 10 as a policy. Lastly, it studies the effects of a recent decline in unionization in teachers' labor market. The existing literature on the topic, including Hoxby (1996); Eberts and Stone (1987); Lovenheim (2009), is fairly limited, and has explored the direct effect of changes in unionization on test scores. In addition, this literature has typically relied on historical episodes of a rise in unionization (due to a lack in recent variation). If the consequences of a decline in unionization are not symmetric to those of an increase, results from this paper can be useful to understand how the teacher labor market changes in response to a weakening of unions and a reduction in the scope of collective bargaining, which could possibly diffuse to other states (such as Illinois) in the immediate

[2] Hanushek et al. (2004), for example, shows that some characteristics of the student body appear to be more important determinants than salaries in the location decision of a teacher.

[3] The literature on financial incentives to teachers has shown sizeable results on student achievement outside the US (Muralidharan and Sundararaman (2011) and Duflo et al. (2012) in India Lavy (2002) in Israel, Atkinson et al. (2009) in England, Glewwe et al. (2010) in Kenya). Plans implemented in the US, however, have failed to yield significant results. Although some studies have found positive effects of performance pay on student test scores (Ladd, 1999; Figlio and Kenny, 2007), most of these programs have been shown to be ineffective at boosting achievement, as shown by Figlio and Kenny (2007); Dee and Keys (2004); Springer et al. (2011); Goodman and Turner (2013); Fryer (2013) (see Jackson et al., 2014; Neal et al., 2011, for a review).

future.

The rest of the paper is structured as follows. Section 2 reviews the literature on teachers, unions, and salaries, and describes the institutional framework surrounding Act 10. Section 3 describes the data. Section 4 discusses the effects of Act 10 on salaries. Section 5 shows evidence on teachers' responses to Act 10s. Section 6 discusses the effects of Act 10 on student achievement. Section 7 presents the structural model, estimates of the parameters, and the implied elasticities. Section 8 studies the effect of counterfactual policies on salaries on the composition of the teaching workforce. Section 9 concludes.

2 Teachers, Unions, and Salaries: Institutional Background and Related Literature

2.1 Teacher Unions and Salaries in the US

Teacher unions were created in the early 1900's from the conversion of existing teacher professional associations, to address social and educational issues relevant at the time (Murphy, 1990; Hoxby, 1996). Among these issues were higher teacher salaries, tenure rights, and pensions.[4]

Currently, teacher unions conduct collective bargaining on behalf of their members with federal, state, and local officials over salaries, benefits, and working conditions, playing an active role in shaping the teaching profession.[5] Schools are unionized on a district-by-district basis. Nearly all public school districts have a teacher organization, typically affiliated with one of the largest national unions (NEA and AFT).[6]

Salaries of teachers in US public schools are typically determined using a lock-step salary schedule. This schedule specifies the salary of each teacher as a function of her academic qualifications (e.g. holding a Bachelor or a Master degree) and years of seniority (Podgursky, 2006), and is designed as a matrix listing seniority levels on the rows (steps), and academic credentials on the columns (lanes). Each cell of this matrix specifies the salary earned by all the teachers with a given level of seniority and academic credentials. Movements along steps and lanes are associated with increases

[4]See (Holcomb, 2006) for details on the history of the National Education Association, the largest union in the country. Information on the American Federation of Teachers, the second-largest, is available at http://www.aft.org/about/history.

[5]Forty-nine percent of public school teachers belong to at least one union as of 2014 (Bureau of Labor Statistics, 2014). In 26 right-to-work states, including Texas, Florida, and Wisconsin, teachers who choose not join the union are not required to pay monthly dues, despite being covered by collective bargaining agreements. In all other states (including California, New York, and Illinois) non-union teachers are also required to pay a fee to the union as a condition of employment.

[6]While collective bargaining is not a constitutional right for public sector teachers, this right is granted by most states. At the time of writing Georgia, North Carolina,South Carolina, Texas, and Virginia did not grant collective bargaining rights to public sector employees.

in salary. In states that allow collective bargaining for public sector employees, these schedules are negotiated between school districts and teacher unions.[7] Collective agreements usually prevent districts from adjusting salaries on an individual basis. As a result, seniority and education are the only determinants of teacher pay, and salaries do not depend on teacher performance.

2.2 Wisconsin's Act 10

There are 422[8] public school districts in Wisconsin, each serving either one city, or one or more towns and villages.[9] As in most US states, each district operates public schools. This includes hiring teachers and allocating them to schools, as well as conducting collective bargaining with the relevant teacher union to establish the conditions of employment, including salaries.[10]

Teacher unions in Wisconsin - as all public sector unions - were very powerful until 2011.[11] In particular, unions were involved in negotiating salary schedules of teachers with the school districts. Under these schemes all teachers in the same district and with the same level of seniority and academic credentials earned the same salary, and individual-specific salaries were prohibited. As an illustration, Figure A1 shows the salary schedule in place in 2011 in the district of Racine.

On June 29, 2011 the State Legislature passed Act 10, which considerably reduced the scope of collective bargaining for public sector unions, including teacher unions. In particular, the Act limits negotiations and collective agreements to base salaries, and explicitly prohibits agreements over the salary schedule. For public school districts this translates into the possibility of individual negotiations with each teacher, effectively creating a "marketplace for teachers".[12] Districts have, however, used the freedom provided by the new law in different ways. Some of them, such as Racine, have continued to determine teacher pay using a seniority-based schedule. Others, such as Green Bay, have discontinued the use of a schedule, and currently negotiate salaries on an individual basis, with the (more or less explicit) goal of rewarding merit and performance.

[7] In states with no collective bargaining, these schedules are typically determined at the state level (e.g. Georgia).

[8] In the period of analysis considered (2006 to 2014) the following groups of districts consolidated into one single district: Trevor Grade School and Wilmot Grade in 2006-2007 (to form the Trevor-Wilmot Consolidated school district), Chetek with Weyerhaeuser in 2010-2011 (to form the Chetek-Weyerhaeuser Area school district), and Glidden and Park Falls in 2009-2010 (to form the Chequamegon school district). The Gresham school district gained independence from the Shawano school district in 2007-2008. Due to these consolidations and separation, the number of districts is 424 in 2006-2009, 423 in 2010, and 422 in 2011-2014.

[9] Each district enrolls 1,900 students on average. On average, 16 urban districts enrolls 15,000 students (with Milwaukee Public Schools enrolling 67,000 students, and the Madison Metropolitan School District enrolling 26,500 students), 63 suburban districts enrolls 3,000 students, and 344 rural districts enrolls 1,000).

[10] In order to become teachers, prospective workers must hold a bachelor degree, complete a teacher education program, and obtain a teaching license. Out-of-state applicants who are already licensed teachers can obtain a license depending on teaching experience, education, and type of license in the state of origin.

[11] With a State act signed by governor Gaylord Nelson in 1959, Wisconsin was the first state to introduce collective bargaining for public sector employees, and has become a right-to-work state only in 2015.

[12] M. Beck, *A teacher "marketplace" emerges in post-Act 10 Wisconsin*, The Wisconsin State Journal. Retrieved from http://host.madison.com/wsj/.

3 Data and Measurement

The main data used in the empirical analysis consists of individual-level information on demographic characteristics, teaching assignments, and salaries of the universe of Wisconsin teachers. I use each teacher's assignment to match this data with information on student enrollment and test scores, recorded at the grade-school-cohort-subject level, and compute measures of teacher quality. In addition, I have collected information on each district's salary regime in place after the passage of Act 10, to understand how each of them implemented the reform.

3.1 Data

Wisconsin Teacher data

Data on the population of Wisconsin teachers is taken from the *PI-1202 Fall Staff Report - All Staff Files* for the academic years 2004-2005 to 2013-2014, published by the Wisconsin Department of Public Instruction (WDPI). This dataset contains information on all individuals employed by the WDPI in each year. Variables include personal and demographic information such as full name, year of birth, education, gender, race, basic information on working history (such as total experience in public schools, as well as experience in the district), information on each job assignment, including total salary, grades served, subject taught, number of contract hours, full-time equivalency (FTE) units, and identifiers for the school and the district each teacher is assigned to. I restrict the sample to non-substitute teachers working in 422 public school districts in Wisconsin. I normalize salaries to full-time equivalents and to 180 days of contract per year, to account for differences between part-time and full-time teachers and between teachers working a smaller number of days. In addition, I exclude teachers whose salaries fall in the top and bottom 1 percent of the salary distribution, to account for errors in the measurement of days of contract and FTE units.[13] To determine mobility across schools, each employee is assigned to the school corresponding to his or her higher level of full?time equivalency units in any given year.

Table 1 shows summary statistics of the final sample of teachers, separately for the years 2006 to 2011, before the passage of Act 10, and 2012 to 2014. The sample covers a total of 92,342 teachers, 78,307 observed between 2006 and 2011, and 66,849 observed between 2012 and 2014. The size of the sample is slighly decreasing over time, with 58,525 teachers in 2006, 57,272 in 2010, and 54,484 in 2014. Approximately 73.4 percent of teachers are women in the sample, including 73.1 percent

[13]The sample entirely excludes teachers employed in the Kenosha school district, as teacher salary data for this district for the year 2010-2011 contain evident recording mistakes.

until 2011 and 74.3 percent after 2011. Teachers have 14.78 years of experience on average, including 14.88 until 2011 and 14.47 after 2011. Overall, 47.4 percent of teachers hold a bachelor's degree, 52.0 hold a Master degree, and only 0.2 percent hold a Ph.D. These shares are equal to 48.5, 50.9, and 0.2 percent until 2011, and to 43.9, 55.3 and 0.2 percent after 2011. Average FTE-adjusted nominal salaries increase from $50,620 between 2006 and 2011 to $53,693 after 2011. The share of teachers moving to a different district increases from 2.2 percent between 2006 and 2011 to 3.5 percent after 2011. A share of 3.8 percent of teachers leave public schools teaching each year until 2011, and 5.2 after 2011. This share includes teachers who change job, start teaching in private schools, and retire.

School Data

I match teacher data with school-grade level data using on job assignments. School data is taken from the Wisconsin Information System for Education (WISE), and includes total enrollment, as well as a breakdown of enrollment into different classes of students, defined by gender, socioeconomic status, disability status, race, and ethnicity. This information is useful to determine the characteristics of the population of students served by each school and district, and is used in the estimation of teacher value-added.[14]

Student Achievement data

Publicly available data on student achievement includes student performance in Mathematics, Reading, English, Language Arts, Science, and Social Studies in grades 3-8, and 10. This data is available as average scale scores in the Wisconsin Student Assessment System (WSAS) at the school-grade-subject level.[15] Achievement data in Mathematics and Reading for grades 3-8 and 10 is used to compute teacher value-added.

3.2 Measurement: Teacher Value Added

Analyses of the selection patterns of teachers across school districts and in and out of public schools require a measure of teacher quality. In line with the previous literature (Hanushek, 1971; Rockoff, 2004; Rivkin et al., 2005; Chetty et al., 2014a) I measure teacher quality using value-added, defined

[14] In Wisconsin students can attend school in the district in which they reside. An open enrollment program exists, for which students can apply for enrollment in a non-resident district conditional on seats availability. Enrollment in non-resident districts is not, however, guaranteed. Less than 5 percent of students applied for open enrollment in 2015.

[15] The WSAS is a comprehensive statewide program designed to provide information about "[...]what students know in core academic areas and whether they can apply what they know[...]" (Wisconsin Department of Public Instruction, available at http://dpi.wi.gov/wisedash/about-data/assessment). It includes: the Wisconsin Forward Exam at grades 3-8 in English Language Arts (ELA) and Mathematics, and at grades 4, 8, and 10 in Science; the New Assessment (TBD) at grades 4, 8, and 10 for Social Studies; the Dynamic Learning Maps (DLM) at grades 3-11 in ELA and Mathematics, and at grades 4 and 8 - 11 in Science; the ACT Aspire at grades 9 and 10; the ACT Plus Writing at grade 11 for Reading, English, Mathematics, Science, and Writing, and the ACT WorkKeys at grade 11.

as the individual teacher's contribution to achievement growth. This "teacher effect" is identified and calculated as one of the component of residual test scores, once other determinants of achievement are taken into account.

I estimate teacher value-added as a time-invarying measure using the Bayes estimate proposed by Kane and Staiger (2008), and further developed by Chetty et al. (2014a). The nature of student achievement data, available only at the grade-subject level for the state of Wisconsin, and the presence of multiple classrooms (and therefore multiple teachers) in each school and grade, makes it impossible to exactly match teachers with the students they taught. This poses a challenge to the estimation of this measure. The nature of the data makes it impossible to separately identify value-added of teachers who are always employed in the same group of workers: These teachers will therefore all be assigned the same estimate, equal to the average value-added of teachers in the group. As a consequence of this, my estimates are noisier than the ones used in previous papers. In addition, the impossibility of exactly matching teachers with the students they taught (but only with all the students in the same grade and school) is an additional source of measurement error. I estimate value-added as a time-invarying measure of teacher quality, as in Kane and Staiger (2008), using pre-Act 10 data to leave out behavioral responses of teachers following Act 10. Details on the procedure used to estimate teacher value-added, as well as a comparison of my estimates with those in the literature, are provided in Appendix D.

3.3 Employee Handbooks and Salary Schedules

Information on the salary schemes in place in each district after Act 10 is taken from districts' Employee Handbooks, publicly available documents used to disclose duties and rights of each public school teacher, including details on how teacher salaries are determined. I have collected each district's Handbook available online as of December 2015, and analyzed these documents to retrieve information on the salary schemes in place after the passage of Act 10. Employee Handbooks are available for 223 out of 422 districts (53%). Taken together, these 223 districts enroll approximately 80% of all Wisconsin students. On average they enroll less disadvantaged students, pay teachers a higher salary, employ less-experienced but better-educated teachers, and are located in areas with lower property values per-pupil, compared with districts for which the Handbooks are not available (Appendix Table A1). The empirical analyses presented in the next sections are based on the subsample of 223 districts with available Employee Handbooks.

I classify each district as salary-schedule if the Handbook contains one and no mention is found on rewards for performance or merit, and as individual-salary otherwise. Intermediate cases where a schedule is published, but there is mention of bonuses linked to performance, are classified as individual-salary districts.

The Racine Metropolitan School District, one of the largest urban district in terms of enrollment, is an example of a salary-schedule district. Even after the passage of Act 10, this district has used a salary schedule to determine teacher salaries. The schedule is published every year as part of its Employee Handbook (Figure A1).[16] In particular, the Handbook specifies that both the initial placement of a teacher on the schedule and movements across steps and lanes are solely determined based on seniority and academic credits.

The Green Bay Area Public School District, the fifth largest Wisconsin district in terms of enrollment, is the largest among the ones that discontinued the use of a salary schedule after Act 10. Its Employee Handbook does not contain any schedule, and it explicitly states that "The District will determine the starting salary for a new employee. Such determination may take into account any prior experience and education."[17] While the Handbook mentions the possibility that teacher salaries might increase in steps over time, there is no mention that such steps shall be solely linked to seniority and/or academic credentials. In particular, the Handbook specifies that "If step increases are part of a position, employees [...] who have provided satisfactory service, as determined by the District, will advance to the next step [...]. An employee may be held to the previous year's step for less than satisfactory performance. An employee may be frozen at his/her previous year's wage rate for more serious issues."

Table 2 shows summary statistics on the characteristics of the two sets of districts before Act 10. Individual-salary districts are more likely to be located in suburban areas, have higher property values are significantly higher in individual-salary districts than in salary-schedule districts. Individual-salary districts enroll 3.9 percentage points fewer disadvantaged students. Students in individual-salary districts also perform better in both mathematics and reading. In addition, teachers in salary-schedule districts are significantly more experienced and less educated (i.e. more likely to hold a B.A. rather than a Master or a Ph.D.), and have lower value-added. Lastly, salaries are significantly higher in individual-salary districts ($52,550 on average) compared with salary-schedule districts ($50,422).

4 Teacher Salaries Before and After Act 10

In this section investigate the direct effects of the reform on salaries across the two groups of districts. I first show that, in individual-salary districts, salary dispersion increased among teachers

[16] See the Racine School District website, for the most recent version of its teacher salary schedule.
[17] See the Green Bay Area Public School District website for the most recent version of its Employee Handbook.

with comparable seniority and academic qualifications. I then investigate to what extent this increase in dispersion can be explained by teacher quality, by correlating salaries with teacher value-added.

4.1 Dispersion in Salaries

To illustrate the increase in dispersion of salaries, I first show evidence on two of the largest urban districts in Wisconsin. The first is the Racine School District, which has continued to use a salary schedule to determine teacher salaries after Act 10 (Figure A1). The second is the Green Bay Area Public School District, which has introduced individual salaries after Act 10. The two districts are comparable in size, enrolling respectively 20,514 and 20,457 students in 2012, and employing 1,392 and 1,381 teachers included in my sample.

Before Act 10, the two districts' schedules appear very similar. Figure 1 shows median salaries and 25-75 interquartile ranges by two-years seniority classes in Racine (grey) and Green Bay (black), for the years 2007-2011 and for teachers holding a Master degree. The two schedules appear very similar before the passage of Act 10 in terms of within-seniority class salary dispersion, although Racine has higher salaries on average. For example, in the Racine School District median salaries are equal to $47,845 for teachers with 5 or 6 years of seniority (with a 25-75 interquartile range of $5,747), and $64,290 for teachers with 29-30 years (with an interquartile range of $4,363). In the Green Bay Area School District, median salaries are equal to $41,556 for teachers with 5 or 6 years of seniority (with an interquartile range of $2,207), and $62,902 for teachers with 29 or 30 years (with an interquartile range of $2,919).

After Act 10 the difference between the two districts' salary schedules is striking, both in levels and degree of dispersion within each seniority class, as shown by the bottom panel of Figure 1. Median salaries in Racine increase slightly for more experienced teachers compared to their pre-2011 levels, while salary dispersion decreases. The interquartile range decreases from $5,747 to $3,884 for teachers with 5 to 6 years of seniority, and from $4,363 to $1,396 for teachers with 29 to 30 years. The figure looks different for Green Bay. Salaries increase considerably more for teachers with less than 10 years of seniority compared with more experienced teachers (from $41,556 to $47,116, or 13 percent, for teachers with 5 or 6 years of seniority, and from $62,902 to $65,256, or 4 percent, for teachers with 29 or 30 years of seniority). Salary dispersion within each seniority class also increases for teachers with less than 10 years of seniority. The interquartile range increases from $2,207 to $9,856 for teachers with 5 to 6 years, and decreases only slightly from $2,919 to $2,396 for teachers with 29 to 30 years. This simple comparison of the structure of salaries across two of the largest individual-salary and salary-schedule districts over time provides suggestive evidence of a change in the salary structure in the former after 2011. In particular, the new scheme involves higher salaries for some teachers with low levels of seniority, and lower salary growth for other high-seniority teachers.

To formally quantify the increase in the dispersion of salaries following the implementation of Act 10, in Table 3 I test the direct effect of the reform on interquantile ranges of log-salary residuals, using quantile regressions and comparing individual-salary and salary-schedule districts before and after 2011 in a difference-in-differences framework.[18]

Estimates indicate a 0.2 percent increase in the interquartile range of individual-salary districts compared with salary-schedule districts after 2011 (25-75, column 1, significant at 1 percent). This increase is larger for teachers with a Master degree (column 2), and especially for those having less than 10 years of experience (column 3), as suggested by Figure 1. This increase in dispersion is entirely driven by an increase in the 50th-25th percentile difference (0.4 percent, column 5, significant at 1 percent). These estimates confirm an increase in salary dispersion in individual-salary districts after 2011 compared with salary-schedule districts, especially for low-seniority teachers. This evidence indicates that the departure from the salary schedule allows teachers with comparable seniority and academic qualifications to earn different salaries. This, in turn, suggests that individual-salary districts use their newly-gained freedom to compensate teachers for attributes not rewarded by a standard lock-step schedule.

4.2 Salaries and Teacher Quality

Teacher quality is a natural candidate as one of the attributes rewarded with higher salaries in individual-salary districts after Act 10. I test this hypothesis by showing that salary residuals and value-added become more correlated after Act 10 in individual-salary districts.

Figure 2 graphically shows the linear fit, together with 90-percent confidence intervals, of the relationship between teacher value-added residuals (horizontal axis) and salary residuals (vertical axis). I exclude teachers having "extreme" value-added estimates, i.e. smaller than -3 and larger than 3 (approximately 1 percent of the sample). [19] The top panel shows that salary residuals are uncorrelated with teacher value-added before Act 10 in all districts: the fit lines are flat and the confidence intervals contain zero both for individual-salary districts (red line) and salary-schedule districts (blue line). The top panel indicates that, after Act 10, the correlation becomes significantly positive in individual-salary districts, whereas it remains indistinguishable from zero in salary-schedule

[18] Log-salary residuals are obtained from a regression of log-salaries on district fixed effects, year fixed effects, and two-years seniority dummies interacted with education dummies.

[19] Residuals are obtained from a regression of salaries or value-added on year fixed effects and two-years seniority dummies interacted with academic qualifications dummies, and estimated separately for each district and for the periods 2007-2011 and 2012-2014. Value-added measures are standardized to have mean equal to 0 and variance equal to 1.

districts.

To formally test this increase in the correlation between salaries and value added I estimate the following regression:

$$\hat{w}_{ijt} = \delta_0 q_{ijt} + \delta_1 \hat{q}_{ijt} * post_t + \varepsilon_{ijt} \tag{1}$$

where w_{ijt} is the residual salary of teacher i employed in district j in year t, q_{ijt} is residual value-added of teacher i employed in district j in year t, and $post_t$ is a dummy for years after 2011. Residuals of salaries and value-added are obtained from a regression of these variables on two-years seniority dummies interacted with education dummies, year fixed effects, and district fixed effects, separately for the years 2007 to 2011, and 2012 to 2014.

Results from this test provide evidence that, after the passage of Act 10, individual-salary districts depart from a seniority-based salary schedule to offer higher salaries to higher-quality teachers. Table 4 shows estimates of the coefficients δ_0 and δ_1. In the full sample of individual-salary and salary-schedule districts, the correlation between salary residuals and teacher value-added is small and insignificant until 2011, and it becomes larger, although not significantly different from zero, after 2011. The post-Act 10 correlation is larger and statistically significant in individual-salary districts, with an estimate of δ_1 equal to 158.6 (Table 4, column 2, significant at 5 percent), and considerably smaller and insignificant in salary-schedule districts (with an estimate of 20.28, Table 4, column 3). The difference in the post-Act 10 correlation across individual-salary and salary-schedule districts is estimated by the triple interaction $IS_j * q_i * post_t$ in column 4 of Table 4, which it is equal to 138.36 (significant at 10 percent). Despite being small in dollar terms, the positive correlation between value-added and salaries signals that individual-salary districts have used their newly-gained freedom in setting salaries to reward teacher characteristics which are, at least in part, correlated with a measure of quality based on test scores.[20]

To shed light on the salary scheme in place in each individual-salary and salary-schedule district before and after Act 10, I estimate the correlation between salaries and value-added, conditional on seniority and academic qualifications, in each district before and after Act 10. I model salaries as follows:

$$w_{ijt} = \gamma_{jt} g(X_{it}) + \delta_{jt} f(VA_i) + \omega_{ijt} \tag{2}$$

where w_{ijt} is the salary earned by teacher i employed by district j in period t, $g(X_{it})$ is a function of

[20] In Appendix Table A2 I also test whether individual-salary districts pay teachers more in fields that usually experience teacher shortage, such as math, technology, bilingual education, and special education. The table shows that, before Act 10, technology teachers earn 0.9 percent more in individual-salary districts and 1.2 more in salary-schedule districts (columns 1 and 2). After Act 10 the only notable difference is that special education teachers earn 0.7 percent more in salary-schedule districts, although the difference in post-Act 10 salaries for these teachers is not statistically significant between the two groups of districts.

teacher i's seniority and academic qualifications, and $f(VA_i)$ is a function of teacher value-added. I consider two time period, 2007-2011 and 2012-2014, and specify $g(X_{it})$ to be a full set of interactions between two-years seniority dummies and academic degree dummies (Bachelor, Master, and Ph.D.). I specify $f(x)$ to be a standard logistic.[21]

I estimate equation 2 separately for each district, and for the years preceding and following Act 10, and obtain estimates of γ_{jt} and δ_{jt}. The distribution of the estimates of the coefficient δ_{jt} is shown in Figure A5.[22] Before Act 10, the distribution appears similar across the two sets of districts, and concentrated around zero. After Act 10, in individual-salary districts estimates range from a minimum of -\$19,267 in Mosinee to a maximum of \$157,868 in Hartford, with a mean of \$670 and a standard deviation of \$11,378. In salary-schedule districts, estimates of δ range from a minimum of -\$115,732 in Prairie Farm to a maximum of \$23,722 in Alma, with a mean of \$99 and a standard deviation of \$7,768.

Specifying salaries as in equation 2 allows me to go beyond a simple separation between individual-salary and salary-schedule districts, and to directly exploit the changes in the distribution of salaries across districts. I use this econometric framework to model and predict salaries used in the estimation of the teacher labor market model presented Section 7.

5 Effects of Changes in Salary Schedule on the Composition of the Teaching Workforce

The differences in salary schemes across Wisconsin districts after the passage of Act 10 changed the characteristics of teachers' job opportunities. These changes might have influenced the decision of each worker on whether to enter teaching, move across districts, or exit public schools. These decisions have a direct effect on the composition of the teaching workforce and, in turn, on student achievement. In this section I show evidence on the sorting patterns of teachers across Wisconsin districts, as well as out of the public education sector, and on the changes in the composition of the teaching body in the aftermath of Act 10.

5.1 Conceptual Framework

I use a simple Roy-model as a conceptual framework to guide the reader's thinking through the effects of changes in salary schemes on the composition of the workforce. I consider two districts, A

[21]The function has the form $f(VA_i) = 1/(1 + \exp\{VA_i\})$. Specifying the function f to be logistic instead of linear prevents the econometric model from predicting unrealistic salaries for teachers with very high or very low value-added. This is especially important in this context, as value-added is measured with error.

[22]In Figure A5 each estimate is weighted by the number of teacher-year observations used in the estimation.

and B, and a continuum of teachers. Districts are identical in terms of size. In each period teachers maximize their utility, a linear function of salaries w, by choosing in which district to teach. Each teacher is denoted by a quality type θ, assumed to be normally distributed with mean μ and variance σ^2.

I consider two time periods, $t = 0$ and $t = 1$, which can be thought of as the pre-reform and post-reform periods. At time $t = 0$ salaries are fixed across teachers and districts and, most importantly, do not depend on a teacher's quality type: $w_A = w_B = \bar{w}$. As districts are identical, teachers are equally distributed between A and B, and the allocation of teachers across districts does not depend on quality. Under these assumptions teachers have no incentives to change district, and the moving rate is therefore zero. At time $t = 1$, I let salaries change in district A to incorporate a quality component. Specifically, salaries are set as follows: $w_A = \alpha\bar{w} + \beta\theta$, with $0 < \alpha < 1$ and $0 < \beta < 1$. Salaries in B are unchanged at $\bar{w}$. I ignore districts' constraints on budget and capacity (i.e. on the maximum number of teachers to be hired), and discuss the implications of these constraints later.

Two simple propositions summarize the implications of the salary change in district A on the sorting patterns of teachers across districts at $t = 1$ (proofs are contained in Appendix C).

Proposition 1. The share of teachers moving across districts increases after a change in the salary scheme in one of the two districts.

Proposition 2. Movers from A to B are negatively selected in the district of origin. Movers from B to A are positively selected in the district of origin.

Intuitively, the introduction of a quality component of teacher salaries in one district changes the optimal location choice of some teachers, leading to an increase in cross-district movements. This happens because the pre-reform scheme of fixed salaries over-compensates lower-quality teachers and under-compensates higher-quality ones compared to a scheme where quality is rewarded. When the latter is introduced in district A, under-compensated, higher-quality teachers working in B will be better off moving to A. Similarly, over-compensated, lower-quality teachers in A will be better off moving to B to maintain their original salary level.

This simple conceptual framework can be extended to account for exit from the teaching profession, by allowing for the existence of an outside labor market denoted by O. This market represents an outside option for teachers currently employed in one of the two districts, such as a teaching job in a private schools, in a different sector, non-employment, or retirement. When employed in O, workers receive a salary $w_O = \gamma\bar{w} + \lambda\theta$. To rule out uninteresting cases, I assume that exit entails no cost, whereas moving entails a cost m. The presence of the outside market guarantees that teachers who remain in public schools at $t = 0$ have quality $\theta < \bar{\theta}$, where $\bar{\theta} = \frac{(1-\gamma)\bar{w}}{\lambda}$. This setup implies the following propositions.

Proposition 3. Under the above assumptions, the share of teachers exiting public schools increases after a change in the salary scheme in one of the two districts.

Prediction 4. Under the above assumptions, exiters from A are negatively selected in the district of origin.

Intuitively, when district A rewards quality at a higher rate than the outside sector, the best teachers among the incumbents will stay, a group of middle-quality teachers will exit, and a group of lower-quality teachers will move to B. When instead the outside sector rewards quality at a faster rate than district A, the best teachers will exit. These cases are disciplined by the parameters α, β, γ, and λ.

The predictions of the model can be directly brought to the data. Before doing this, however, it should be noted that the theoretical framework does not incorporate the decision of each district to hire a specific teacher. Such decision depends on the district's objective function, as well as on the number of teachers to be hired (capacity constraint) and on total expenditure on salaries (budget constraint). If such constraints are binding, and depending on each district's payoff function, in equilibrium there could be cases in which district A is better off hiring a few very high-quality (and therefore expensive) teachers together with other lower-quality (cheaper) teachers. This would affect teacher movements across districts, as well as exits, and should be kept in mind when testing the predictions of this simple conceptual framework. Districts's demand for teachers is explicitly modeled in the richer, two-sided model of teachers' labor market presented in Section 7.

5.2 Comparing Individual-Salary and Salary-Schedule Districts

In the remaining of this section I study the effects of changes in salaries on mobility of teachers across districts and on exit, comparing individual-salary and salary-schedule districts over time. It is important, however, to highlight that each district's decision to use a salary schedule as opposed to individually-negotiated salaries is not random. While a complete understanding of the reasons behind each district's decision is extremely challenging (although not strictly necessary to carry on simple comparisons of teacher and student outcomes across the two districts over time), these reasons become relevant when studying the demand and supply of teachers, as they might depend on districts' objective functions. It is therefore useful to briefly speculate on them.

First, school districts might be maximizing different objective functions when deciding who to hire and how to spend their resources, and consequently adopt different salary schemes. This might be true, for example, if districts serve different pools of taxpayers. Some districts could choose to maximize achievement of all pupils, others could give a higher weight to specific groups of students. Districts might also give different weights to the welfare of teachers (as opposed to that of the students). Second, even districts with identical objective functions could have different beliefs on how to reach their objective. For example, districts might value teacher characteristics, such as value-added, academic qualifications, or seniority, in different ways, and therefore choose to reward them differently. Valuations of these characteristics could also be different across districts with the same objective if, for example, districts serve very different pools of students, and if teachers with certain characteristics vary in their productivity to teach to diverse student bodies (Jackson, 2013). Third, district superintendents and/or school board members, directly responsible for deciding the structure of teacher salaries after Act 10, might be more or less favorable to individual salary plans across districts in a rather idiosyncratic way. As the changes in salaries introduced by Act 10 are relatively recent and were not anticipated, it is reasonable to assume that these administrators were not selected according to their preferences over teacher salaries, and therefore "randomly" assigned to districts with respect to these preferences.[23] Lastly, some districts might simply have been slower to adjust to the new legal framework for idiosyncratic reasons, remaining "stuck" with the old salary schedule. Each of these potential explanations has different implications on the shape of the demand for teachers in each district. A more thorough discussion of the implications of these reasons on teacher demand and supply is deferred to Section 7.

Due to the lack of experimental variation in the structure of salaries across districts after Act 10, estimating the causal effects of the introduction of individually-negotiated salaries on teachers' and students' outcomes requires that the two districts were not different ex-ante, in ways that could have an influence on the selection of teachers and on student achievement. One might worry that, if the decision on post-Act 10 salary structures is driven by administrators' preferences, these administrators were adopting different practices related to the teaching job before the Act was passed. This is unlikely

[23] Act 10 was first introduced to the state legislature on February 14, 2011. A few days later all 14 Democratic members of the Wisconsin State Senate left Wisconsin and traveled to Illinois in order to delay a vote on the bill, leaving the Senate with only 19 Republican members and therefore without the 20 Senators required for a quorum in order to vote on the bill. The bill was eventually passed without the vote of the Democratic Senators, bypassing the quorum rule by removing some provisions from the original text of the Act, and signed into law on March 11, 2011.

for the following reason: these practices, including salaries, instructional practices, and hours were strictly regulated by collective bargaining agreements, and these agreements are very similar across districts. As a result, what administrators with different preferences could do was in practice the same across districts.

The comparison across the two groups of districts relies on two further assumptions. The first is common trends before Act 10. The second is common support of the distribution of observable characteristics across the two groups. I discuss the first assumption separately for each test in the next two sections. In support of the second assumption, Figure A4 (top panel) shows the distribution of a set of district-level characteristics. Despite differences between the average individual-salary district and the average salary-schedule district (Table 2), the distributions of these characteristics across salary-schedule and performance-pay districts have common support. The second assumption is therefore verified.

To partially account for pre-existing differences between salary-schedule and individual-salary districts, I complement a simple comparison of individual-salary and salary-schedule districts with comparisons on a subsample composed by individual-salary districts and matched salary-schedule districts. This sample is obtained using a nearest-neighbor Mahalanobis matching procedure with replacement (Abadie and Imbens, 2002). This procedure matches each individual-salary district with a salary-schedule district that is comparable on the basis of pre-Act 10 characteristics. These include student enrollment, indicators for the district being located in urban or suburban areas, and average property value per-pupil; average salaries for all teachers, and for teachers with less than 5 years and more than 20 years of experience, average teacher experience, share of teachers holding a Master, and share of disadvantaged students. The propensity score is estimated using district-level averages of these variables for the years 2005-2011 (see Table A3 for the estimates of the probit model). Table 2 shows summary statistics of pre-Act 10 characteristics in 101 individual-salary districts and in 64 matched salary-schedule districts. The two groups of districts appear similar in terms of composition of the teaching body, with no significant differences in experience, education, and average value-added, and smaller differences in salaries compared with the full sample. Figure A4 (bottom panel) shows that the distribution of a set of district characteristics across salary-schedule and performance-pay districts appear very similar. The results presented in the next subsections are based on this matched subsample. These results hold on the full sample, as well as on matched samples obtained matching on different sets of observables, and using different matching methods (Tables A4 and A5).

5.3 Movements across districts

In line with Prediction 1, moving rates of teachers sharply increase both across and within the two types of districts (individual-salary and salary-schedule) after 2011, as shown in Figure 3. The share of teachers moving from salary-schedule to individual-salary districts (out of the total number of teachers employed in individual-salary and salary-schedule districts) doubles from 0.4 percent in 2006-2011 to 0.8 percent between in 2012-2014. The percentage of teachers who move in the opposite direction, i.e. from individual-salary to salary-schedule districts, more than doubles from 0.3 in 2006-2011 to 0.7 percent in 2012-2014. The share of teachers who reallocate within salary-schedule districts increases from 0.5 percent in 2006-2011 to 0.8 percent in 2012-2014. Lastly, the share of teachers who reallocate within individual-salary districts increases from 0.4 percent in 2006-2011 to 0.7 percent in 2012-2014. These movements indicate a substantial degree of reallocation across districts in all directions, and slightly higher across districts of different type.[24]

In the top panel of Figure 4 I shed light on teachers' sorting patterns following Act 10, by plotting average value-added of movers by district of origin and destination. Since value-added is used as a dependent variable, for these tests I use estimates without the shrinkage factor, as this would lead to bias (see Appendix D). I instead weigh each observation by the shrinkage factor, avoiding bias but at the same time giving more weight to more precisely estimated value-added estimates. Lastly, I exclude teachers having "extreme" value-added estimates, i.e. smaller than -3 and larger than 3 (approximately 1 percent of the sample). Consistently with Prediction 2, the figure shows an increase in quality of movers from salary-schedule to individual-salary districts, and a decrease in quality of movers from individual-salary to salary-schedule districts. Value-added of teachers moving from salary-schedule to individual-salary districts increases from -0.145 in 2010-11 to 0.183 in 2012-13 and 0.112 in 2014 (black line). Average value-added of teachers moving from individual-salary to salary-schedule districts, on the other hand, declines from 0.075 in 2010-11 to 0.021 in 2012-13, and 0.044 in 2014 (gray dashed line). The difference in the two series, together with confidence intervals, is shown in the bottom panel of Figure 4.

I formally test these sorting patterns by comparing value-added of movers to individual-salary and

[24]Movements of teachers across districts of the same type might be due to an increase in the number of vacancies, caused by teachers moving out to a different type of district or exiting, and motivated by preferences of teachers for other attributes of a job. In addition, movements within individual-salary districts might be due to potentially important differences in salaries faced by teachers across districts of this type, which are not captured by the binary classification of districts into salary-schedule and individual-salary. To overcome the limitations of this simple classification, in Section 7 I use the empirical distribution of salaries in each district to characterize each district's salary scheme and to estimate a model of the teacher labor market.

salary-schedule districts, before and after Act 10, in a difference-in-differences framework:

$$q_{ijt} = \beta_0 + \beta_1 IS_j + \beta_2 IS_j * post_t + \tau_t + \varepsilon_{ijt} \tag{3}$$

where q_{ijt} is value-added (expressed in standard deviations) of teacher i, moving to district j in year t, IS_j equals 1 for individual-salary districts of destination, $post_t$ equals 1 for years after 2011, τ_t is a vector of year fixed effects, and ε_{jt} is the error term. The parameter β_2 captures the change in the difference in value-added of movers to individual-salary districts compared with movers to salary schedule districts following Act 10. I estimate the model on the subsample of movers from salary-schedule to individual-salary districts and movers in the opposite direction.

Results from this test, shown in Table 5, confirm the suggestive evidence of Figure 4: in the aftermath of Act 10, higher-value-added teachers move from salary-schedule to individual-salary districts, compared with movers in the opposite direction. Estimates of the parameter β_2 indicate that value-added of movers from salary-schedule to individual-salary districts is 33.9 percent of a standard deviation higher compared with that of teachers moving from individual-salary to salary-schedule districts (Table 5, column 2, significant at 10 percent). Estimates of β_2 on the full sample of districts are smaller but still positive, with an estimate of 17.6 percent (Table 5, column 4, p-value equal to 0.16).

Movers and incumbents

To shed light on how the sorting patterns of movers affect the composition of the teaching workforce in each district, I compare movers with incumbent teachers in the district of destination. I estimate the following model separately for individual-salary and salary-schedule districts:

$$q_{ijt} = \beta_1 m_{it} + \beta_2 m_{it} * post_t + \theta_j + \tau_t + \varepsilon_{jt} \tag{4}$$

where q_{ijt} is value-added of teacher i working in district j in year t, m_{it} equals 1 if teacher i changes district in year t, and θ_j is a vector of district fixed effects. Estimates of the parameter β_1 capture the difference in value-added between movers and incumbents within each district of destination until 2011. Estimates of the parameter β_2 capture changes in this difference after Act 10.

Estimates of the parameters suggest that, in the aftermath of Act 10, movers to individual-salary districts become more positively selected in the district of destination compared with movers to salary-schedule districts. An estimate of β_1 equal to -0.055 for the subsample of individual-salary districts indicates that movers to these districts were negatively selected compared with incumbents until 2011

(Table 6, column 1, significant at 5 percent). An estimate of β_2 equal to 0.051 indicates that this negative selection is partially offset after Act 10, although estimated imprecisely (Table 6, column 1, p-value equal to 0.33). In the sample of matched salary-schedule districts, on the other hand, an estimate of β_2 equal to -0.051 suggests that movers become more negatively selected after 2011 (Table 6, column 2). The post-2011 difference in the selection of movers in the district of destination between individual-salary and salary-schedule districts is estimated by the triple interaction *IS * mover * post*. An estimate of 0.112 on the matched sample suggests that the selection of movers in individual-salary districts improves after Act 10 compared with salary-schedule districts (Table 6, column 5, p-value equal to 0.23). Taken together, these results provide a first piece of evidence in favor of an improvement in the composition of the teaching workforce in individual-salary districts compared with salary-schedule districts.

Salaries of movers

Having determined the patterns of selection of teachers moving across districts, I now show that these movements can be motivated, at least in part, by an increase in salaries. I estimate the following regression:

$$\log(w_{ijt}) = \gamma_0 m_{it} + \gamma_1 m_{it} * post_t + \delta X_{it} + \mu_i + \theta_j + \tau_t + \varepsilon_{ijt} \tag{5}$$

where w_{ijt} is salary of teacher i, employed in district j at time t, m_{it} equals one if teacher i changes district in year t, X_{ij} is a vector of teacher controls including dummies for two-years seniority classes interacted with dummies for holding a Bachelor, Master, or Ph.D., and μ_i is a vector of individual fixed effects. In this specification the coefficient γ_0 captures the average increase in salaries experienced by teachers in the year in which they change district, and γ_1 captures the change in this increase after Act 10.

Results from this test suggest that the increase in movements of high-quality teachers to individual-salary districts after Act 10 could, at least in part, be motivated by an increase in salaries. The first three columns of Table 7 show estimates of this equation on the sample of teachers working in individual-salary and salary-schedule districts. Before Act 10 movers to individual-salary districts experienced a significant 2.1 percent decrease in salaries upon moving. After Act 10, however, this negative change is offset by a 2.0 percent increase in salaries upon moving (Table 7, column 1). In the subsample of matched salary-schedule districts, movers experienced a 1.3 percent decrease in salaries until 2011; after Act 10, however, salaries of movers increase only by 0.8 percent (Table 7, column 2). The interaction coefficient *mover * IS * post* in columns 4-5 of Table 7 tests for the difference in the post-Act 10 increase in salaries of movers to the two types of districts. An estimate of 1.5 percent on the matched subsample indicates that movers to individual-salary districts experience a significantly larger increase in salaries upon moving after Act 10 compared with movers to salary-schedule districts (Table 7, column 4, significant at 5 percent).

5.4 Exit from public schools

Figure 5 shows trends over time in the share of teachers exiting individual-salary and salary-schedule districts, and provides evidence of a large increase in the exit rate of teachers from both types of districts following Act 10, slightly larger in individual-salary districts.[25] In salary-schedule districts 1.9 percent of teachers exit in 2010 and 2011. In 2012 this share increases to 3.2 percent, and remains high at 3.5 percent until 2014. By comparison, 1.5 percent of teachers working in individual-salary districts exit in 2011. In 2012 this share rises to 2.7 percent, and remains high to 2.3 percent until 2014.

To explore how exit affects the composition of the teaching workforce after Act 10, the top panel of Figure 6 shows average value-added of exiters by type of district of origin. Value-added of teachers exiting from individual-salary districts is equal to 0.053 in 2010-11, and decreases to -0.015 in 2012-2013 and -0.031 in 2014 (black line). Value-added of exiters from salary-schedule districts is instead equal to 0.001 in 2010-2011, and it increases to 0.113 in 2012-2013, and to 0.020 in 2014 (dashed gray line). The difference in the two series, together with confidence intervals, is shown in the bottom panel of Figure 6. This figure indicate that low-quality teachers are disproportionately more likely to exit individual-salary districts after Act 10 compared with salary-schedule districts, possibly discouraged by the perspective of lower salaries or slower salary growth.

In Table 8 I formally test these exit patterns by comparing value-added of exiters from individual-salary and salary-schedule districts, before and after Act 10, in a difference-in-differences framework. The results confirm the evidence in Figure 6: An estimate of -0.1654 for *IS * post* indicates that average value-added of teachers exiting from individual-salary districts after 2011 is 16.5 percent of a standard deviation lower compared with that of teachers leaving salary-schedule districts (Table 8, column 2, significant at 5 percent). This result holds also in the full sample (Table 8, column 4).

Exiters and stayers

In Table 9 I compare value-added of exiters with value-added of stayers within each district of origin. Results confirm that exiters from individual-salary districts are negatively selected after Act 10: Their exit positively affects the overall composition of the workforce in these districts. Value-added

[25] I define a teacher as exiting Wisconsin public schools if she drops out of the sample in any given year.

of exiters from individual-salary districts is, if anything, higher compared with value-added of stayers until 2011. After 2011, however, value-added of exiters is 6.5 percent of a standard deviation *lower* compared with value-added of stayers in these districts (Table 9, column 1, significant at 10 percent). By comparison, value-added of exiters from the matched sample of salary-schedule districts is 8.96 percent higher compared with value-added of stayers after 2011 (Table 9, column 2, significant at 10 percent). The post-2011 difference in value-added of exiters relative to stayers between individual-salary and salary-schedule districts is estimated by the triple interaction *IS * exiter * post* in column 4 of Table 9. An estimate of -0.1532 for the matched sample confirms that exiters from individual-salary districts become more negatively selected after Act 10 compared with exiters from salary-schedule districts (significant at 5 percent).

Salaries of exiters

I now show that the increase in exit of low-quality teachers from individual-salary districts after Act 10 can be partly motivated by a drop in their salaries after Act 10. I estimate the following regression:

$$\log(w_{ijt}) = \gamma_0 e_{it} + \gamma_1 e_{it} * post_t + \delta X_{it} + \mu_i + \theta_j + \tau_t + \varepsilon_{ijt} \tag{6}$$

where e_{it} equals one if teacher i exits at the end of year t. In this specification the coefficient γ_0 captures the average increase in salaries experienced by teachers right before exiting, and γ_1 captures the change in this increase after Act 10.

Table 10 shows estimates of this equation on the sample of teachers working in individual-salary and salary-schedule districts. Before Act 10 exiters from both types of districts experience a significant decrease in salaries before exiting (estimate of *exit*, Table 10, columns 1-2). After Act 10, however, this decrease becomes 1.1 percentage points larger in individual-salary districts (estimate of *mover * post*, Table 10, column 1, significant at 5 percent), whereas no change can be noted in salary-schedule districts (Table 10, column 2). The interaction coefficient *exit * IS * post* in column 4 of Table 10 tests for the difference in the post-Act 10 change in salaries of exiters from the two types of districts. An estimate of -2.1 percent on the matched subsample indicates that exiters to individual-salary districts experience a significantly larger drop in salaries right before exiting after Act 10, compared with exiters from salary-schedule districts.

5.5 Composition of the teaching workforce

Figure 7 shows that increased movements of teachers across districts after Act 10, as well as exit from public schools, led to an improvement, albeit small, in the composition of the teaching workforce in individual-salary districts after 2011 compared with salary-schedule districts. Average value-added of teachers in individual-salary districts slightly increases from 0.008 in 2010-2011 to 0.010 in 2012-2013 and 2014 (Figure 7, black line). Average value-added of teachers in salary-schedule districts, on the other hand, declines from 0.010 in 2010-2011 to 0.009 in 2012-2013, and -0.003 in 2014 (Figure 7, gray dashed line).

To formally test these differences I adopt a difference-in-difference framework to compare value-added of teachers employed in individual-salary and salary-schedule districts before and after Act 10. Although estimated imprecisely, the coefficient on the interaction term *IS * post* on the matched sample is positive and equal to 0.005, indicating a 0.5 percent of a standard deviations improvement in the composition of the teaching workforce in individual-salary districts compared with salary-schedule districts following Act 10 (Table 11, column 3, p-value equal to 0.51).

Although imprecise, these tests confirm that the changes in teacher salary schemes in individual-salary districts after Act 10 led to an improvement in the composition of the teaching workforce. The small size of such improvements is due to the fact that, in absolute terms, the rates of movements and exits of teachers are rather small. Despite the lack of precision, these results provide suggestive evidence that changes in salary schemes in some districts can have an effect on the composition of the workforce, and that a sustained growth in the moving and exit rates of teachers over time could make these compositional changes larger in the medium run.

6 Effects on Student Achievement: Composition of the Workforce vs. Effort

As teachers are the most important input in the production of student achievement and responsible for the largest part of the variation in test scores (Rockoff, 2004; Jackson et al., 2014; Chetty et al., 2014a), changes in the composition of the teaching workforce such as the ones documented in the previous section can potentially have a large effect on achievement.

Figure 8 plots average standardized test scores for math, reading, and language arts, in individual-salary and salary-schedule districts over time.[26] In individual-salary districts, math test scores are steadily increasing over time (top panel, black line), whereas in individual-salary districts they follow an upward time and flatten after 2011 (top panel, gray dashed line). The difference in math achievement widens in the aftermath of Act 10

[26] Test scores are available for grades 3 to 8, and 10, separately for each grade, school, and cohort. Means are computed weighing observations by the number of students in each grade, school and cohort. Test scores are standardized with respect to the 2009 state-wide distribution of test scores, separately for each subject and grade. Results are robust to standardizing test scores with respect to the distribution in other pre-Act 10 years.

To formally estimate the achievement gains experienced by individual-salary districts compared with salary-schedule districts after Act 10, I estimate the following difference-in-differences model, separately for each subject:

$$A_{gsdt} = \beta IS_d * post_t + \gamma Z_{gsdt} + \tau_t + \epsilon_{gsdt} \quad (7)$$

where A_{gsdt} is average test scores of students in grade g, school s, district d, and year t. The vector Z_{gsdt} includes a set of school and grade fixed effects, to account for time-invarying differences in achievement within these groups.

Estimates of the parameter β on the matched sample of individual-salary and salary-schedule districts indicate that math test scores of students in individual-salary districts are 6.3 percent of a standard deviation higher after 2011 compared with salary-schedule districts (Table 12, column 1, significant at 10 percent). By comparison, reading test scores are 3.2 standard deviations higher, and language arts test scores are 1.9 percent higher, although these differences are estimated imprecisely (Table 12, columns 2-3).[27] The magnitude of these effects can be interpreted by comparing it to the achievement gains associated with a 10 percent reduction in class size, which typically corresponds to a 10 percent increase in per-pupil expenditure, and which have been found to be equal to 4 percent of a standard deviation at a maximum (Hoxby, 2000; Angrist and Lavy, 1997).

6.1 Decomposing Changes in Student Achievement

The observed gains in student achievement experienced by individual-salary districts after Act 10 can in part be attributed to changes in the composition of the teaching workforce across districts. It is important, however, to recognize that other factors might be at play in driving these differences. The first is a change in teacher effort. Act 10 provided school districts with the possibility of rewarding merit and performance through higher salaries, in order to attract, retain, and motivate the best teachers. Changes in salaries might therefore have affected teachers' incentives and performance and, in turn, student achievement. Second, as mentioned above, Act 10 has changed some of the main features of a teaching job. This could have had an effect on the selection of workers into the profession. This effect, however, would not be captured by the compositional changes documented in the previous section, as these are based on measures of value-added, unavailable for new teachers.

To assess the extent to which the observed achievement gains experienced by individual-salary districts after Act 10 are due to the observed improvements in the average quality of the teaching

[27] Larger effects of teacher composition on math achievement are in line with previous work (see Jackson et al., 2014, for a review), and consistent with the idea that, while English and reading are learned to a greater extent outside of school, mathematics learning is almost entirely concentrated in the classroom.

workforce, I isolate the change in test scores that cannot be attributed to compositional changes. To do this, I extend equation 7 to include a semi-parametric function of teacher value-added, to account for variation in the composition of the teaching workforce across schools, grades, and years.

Controlling for quartiles of the value-added distribution yields an estimate of β on the matched sample equal to 5.5 percent of a standard deviation for math test scores (Table 12), column 4,significant at 10 percent). Compared with an estimate of 6.3 percent in the basic specification, this indicates that at least 13 percent of the observed change in achievement is due to changes in the composition of the teaching workforce. Overall, 0.8 percentage points of a standard deviation of test scores are explained by changes in teacher composition (difference between the coefficients on *IS * post* in coumns 4 and 8 of Table 12). These results indicate that the observed change in achievement experienced by individual-salary districts after 2011 compared with salary-schedule districts is only partly attributable to changes in the composition of the teaching workforce. The estimated effect of the change in teacher selection on test scores is, however, in line what a simple model of achievement production would predict. Since one standard deviation of my estimates of value-added (without shrinkage) explains at most 15 percent of a standard deviation of test scores in my sample (see Table A7), and since average value-added increases by about 1 percent of a standard deviation in individual-salary districts after Act 10 compared with salary-schedule districts (Table 11), the observed compositional change should be associated with a 0.15 percent of a standard deviation increase in test scores, which is smaller than the increase that can be observed in the data (0.8 percent, or the difference between 6.3 and 5.5 percent).[28]

These results should, however, be interpreted with two caveat. The first is that the estimates of value-added used in the analysis contain measurement error. The estimated effects of changes in value-added on student test scores are therefore affected by attenuation bias. For this reason, the 6 percent estimate of the share of achievement gains attributable to compositional changes should be interpreted as a lower bound.[29] The second is that, changing teachers' working conditions, Act 10 might have influenced the supply of new teachers. The measured compositional changes, however, do not incorporate changes in teacher supply, as value-added is not available for new teachers.

[28] Macartney et al. (2016) decompose the effect of teachers' ability and effort on test scores, building a structural model and exploiting a change in incentives in exerting effort generated by the provisions of the No Child Left Behind (NCLB) legislation in North Carolina. Their results indicate that the selection of high-ability teachers explains a larger part of the variation in test scores than changes in teachers' effort. These results can be reconciled with the ones presented here by recognizing that Act 10 provided teachers with a different type of incentives, through changes in salaries, than NCLB, and that the effects of these changes on the composition of the workforce are, albeit relevant, small in magnitude due to intrinsically low mobility and exit rates of teachers.

[29] The presence of measurement error can be highlighted by noting that the standard deviation of value-added is equal to 0.2 percent of a standard deviation of test scores in Kane and Staiger (2008) and Chetty et al. (2014a), but only 0.15 at a maximum in my estimates.

7 A Model of The Teacher Labor Market

The empirical evidence on teachers sorting across districts and out of public schools in the aftermath of Act 10 suggests that labor market decisions of teachers are influenced by changes in the structure of teacher salaries. As a result, these changes can have important effects on the level of quality of the workforce, and on student achievement. A deeper understanding of the mechanisms that shape teacher labor market decisions is fundamental to design policies aimed at attracting and retaining high-quality teachers, or teachers with certain characteristics, in schools and districts that need them the most, and at increasing their rate of retention. This requires a careful study of teacher labor supply. The matches between teachers and districts analyzed in Section 5 are the outcomes of the interplay of demand and supply forces, which cannot be disentangled using a simple reduced-form approach. To address this limitation I explicitly model and estimate teacher demand and supply in a two-sided choice model.

The model is an extended version of the simple Roy model outlined above, and it is designed as follows. Teachers supply labor to districts and have preferences over the characteristics of each job, such as salary, distance from the previous job, type of district (urban, suburban, or rural), and the composition of the student body. Districts hire teachers to maximize a payoff function that depends on teachers' attributes, such as experience, academic credentials, and value-added, and are subject to a budget constraint on total salaries to be paid, and to a capacity constraint on the total number of teachers to be hired. Each side of the market maximizes its payoffs and, as a result, matches are formed. After solving the model I use the matches observed in the data, together with the cross-district variation in salary schemes introduced by Act 10, to estimate the parameters of demand and supply in this market.

While explicitly designed to capture and replicate the sorting patterns observed in the data, the model contains some limitations in its ability to fully capture the dynamics of teachers' labor market. First, in the model teachers cannot choose their level of effort, and decide where to teach based on that. Second, the model does not allow teachers to have a comparative advantage in teaching in a certain district. Third, the presence of an outside option for teachers is able to generate exit in the model. This option is, however, assumed exogenous and constant across teachers; in particular, the model does not allow for teachers of different age and/or quality to have different options. While these issues are extremely important, a full-fledged analysis on the effects of a policy such as Act 10 on them is left to future research.[30]

[30]Existing research on this topic includes, among others, Dolton and Van der Klaauw (1999), who affirm the importance of teacher salaries and opportunity wages in the turnover decision of teachers and illustrate the insight gained

Estimating teacher preferences over job characteristics is useful for several reasons. For example, it allows to attach a monetary value to non-salary characteristics of a job, and to calculate compensating differentials required to induce high-quality teachers to move from one district to the other. From a policy perspective, this can be helpful to design salary schemes aimed at addressing issues of selection and retention of teachers in hard-to-staff schools and subjects. In addition, calculating how much each district must spend on salaries to hire teachers with certain characteristics can be useful to understand how to redistribute resources across school districts. Lastly, estimates from the model can be used to simulate the effects of alternative salary schemes on the composition of the teaching workforce, as I do in Section 8.

Issues with Hedonic Models and Reduced-Form Approach

Before describing the details of the model, it useful to clarify why a two-sided model is helpful to study teacher preferences. Most previous studies of teacher labor markets, such as Antos and Rosen (1975), employ a hedonic salaries approach to estimate teacher labor supply. This approach relies on the consideration that, if salaries are set to clear the market, then salaries and teacher-district matches observed in equilibrium are implied by the preferences of teachers and districts, and can be used to derive them. When used to estimate the features of teacher labor markets, however, hedonic models might fail. This happens because teacher salaries are quite rigid and unable to fully adjust for differences in both the attributes of workers and the non-pecuniary attributes of their jobs, and cannot be directly used to estimate teacher preferences.

Another argument in favor of a more reduced-form approach to the estimation of teacher labor supply is that, when salary schemes are assumed exogenous, the parameters of a teacher's utility can be estimated using a simple one-sided discrete choice model. This strategy, however, relies on observing the offer set faced by each teacher. The unavailability of this type of information makes it impossible to correctly derive preferences, and requires an explicit modeling of the demand side of the this labor market.

To partially overcome the limitations of a hedonic salary approach and a reduced-form approach to the estimation of teacher labor supply, I build a two-sided model which endogenously generates a set of job offers for each teacher. This empirical exercise is similar to the one by Boyd et al. (2013), who use a many-to-one matching model to estimate teacher preferences. My paper builds on this approach in two ways. First, I model districts' choices as the outcome of a constrained maximization

from differentiating between multiple destinations or exit types; Boyd et al. (2005); Goldhaber et al. (2011), who find heterogeneity in mobility behavior across the performance distribution and evidence that teacher mobility is affected by student demographics and achievement.

problem, explicitly incorporating a budget constraint and a capacity constraint. Second, I estimate my model exploiting the unique variation in salaries caused by the end of collective bargaining over salary schedules and the introduction of individual salaries in Wisconsin in the years following 2011.

7.1 Model Setup

I model the teacher labor market as a two-sided (teacher-district) choice model. In this framework job vacancies arise exogenously in each school district. The process of matching between teachers and districts develops in two steps. First, each district decides whether to make an offer to each teacher. Second, teachers choose which position to accept (if any) among the set of job offers they receive. Job matches are realized as a result.

7.1.1 District's Problem

District j's payoff from hiring teacher i, u_{ij}, is a function of teacher characteristics such as experience, academic credentials, and teacher value-added. This assumption can be rationalized by a model in which districts want to maximize a function of student achievement, which is in turn an additive function of teacher characteristics. Payoffs are additive: the total payoff of district j from hiring a set T_j of teachers is simply the sum of the payoffs from hiring each teacher, $U^j(T_j) = \sum_{k \in T_j} u_{ik}$. In each period district j makes a hiring decision, i.e. selects a vector $o_j = [o_{1j}, o_{2j}, ..., o_{Nj}]$ of offers to each of the N teachers in the labor market, where $o_{kj} = 1$ if a job offer is made from district j to teacher k. I assume that district j has a salary budget B_j and can hire a maximum of H_j teachers. The problem faced by the district is as follows (I omit the subscript j for notational convenience):

$$\max_{\{o_i\}_{i \in N}} \sum_{i=1}^{N} h_i o_i u_i \tag{8}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} h_i o_i w_i \leq B \tag{9}$$

$$\sum_{i=1}^{N} h_i o_i \leq H \tag{10}$$

$$o_i \in \{0,1\} \ \forall i = 1,..,N \tag{11}$$

where h_i is the probability that teacher i accepts the district's offer, if one is made. In words, each district maximizes the *expected* payoff from making a set o of offers, where the expectation is taken with respect to the probability of acceptance. Constraints 9 and 10 are "soft" constraints, i.e. they must only hold in expectation. Intuitively, district incorporate the fact that, once an offer is made to a teacher i, it is only accepted with probability h_i. Since offers are made simultaneously, districts choose the offer set that maximizes their expected payoff and, in expectation, allows them to spend at most B and hire at most H teachers.

Solving the District's Problem

Each district's problem can be solved using linear programming techniques. The problem can be seen as a two-constraints version of the 0-1 knapsack problem, extensively studied in fields such as applied mathematics, operation research, and computer science.[31] A solution algorithm to the one-constraint version, based on the "continuization" of the discrete problem, was proposed by Dantzig (1957). More recently, Martello and Toth (2003) have proposed a similar algorithm to solve the two-constraints version. I apply their procedure to solve the district's problem.

The solution is based on the continuous relaxation of the original problem, which substitutes the constraint in 11 with the milder $0 \leq o_i \leq 1 \; \forall i = 1, .., N$. This allows me to assign a Lagrange multiplier λ to constraint 10. The continuous relaxation of the original problem can then be rewritten as a function of λ:

$$\begin{aligned} &\max_{\{o_i\}_{i \in N}} \sum_{i=1}^{N} h_i o_i (u_i - \lambda) + \lambda H \\ \text{s.t.} \quad &\sum_{i=1}^{N} h_i o_i w_i \leq B \\ &0 \leq o_i \leq 1 \; \forall i = 1, .., N \end{aligned}$$

For each value of λ, this continuous relaxation is a one-constraint version of the unbounded knapsack problem (Dantzig, 1957), which can be solved in a straightforward way using linear programming techniques.[32]

The solution procedure is as follows. First, I define a teacher's *relative payoff* as the payoff the district obtains from hiring her (net of the shadow price of relaxing the capacity constraint) per dollar of salary: $(u_i - \lambda)/w_i$. Intuitively, the relative payoff measures the "efficiency" of the hire from the standpoint of the district. I then sort teachers in descending order of relative payoff, so that $(u_i - \lambda)/w_i \geq (u_{i+1} - \lambda)/w_{i+1}$. This ranking incorporates the fact that the payoff from a hire contains both a monetary cost, captured by the salary that must be paid, and a utility cost, which stems from the the capacity constraint becoming tighter.

Given this sorting, the "critical" teacher is the one indexed by $s(\lambda) = \min\{i : \sum_{j=1}^{i} w_j h_j >$

[31] The name of the problem derives from its most famous application: given a fixed-size knapsack and a set of items, each with a size and a value, determine which items to put in the knapsack so that the total size is less than or equal to the size of the knapsack and the total value is as large as possible (Dantzig, 1957).

[32] As in all linear programming problems, existence of a solution follows from the feasibility of the problem, i.e. the existence of a set of offers that satisfies both constraints, which is easily verifiable in this case.

B or $h_i(u_i - \lambda) < 0\}$. In words, the critical teacher is the first teacher whose hire is unworthy from the point of view of the district, either because the hire leads to a violation of the budget constraint, or because the payoff from the hire is smaller than the utility cost from tightening the capacity constraint. The position of the critical teacher in the ranking separates teachers whose hire is worthy ($i < s(\lambda)$) from teachers whose hire is unworthy ($i > s(\lambda)$). The solution to the continuous relaxation of the problem can then be written as follows:

$$o^{c^*}(\lambda) = \begin{cases} 1 & \text{if } i < s(\lambda) \\ c - \frac{\sum_{j=1}^{i-1} w_j}{w_i} & \text{if } i = s(\lambda) \text{ and } h_i(u_i - \lambda) \geq 0 \\ 0 \text{ if } i = s(\lambda) & \text{and } h_i(u_i - \lambda) < 0 \text{ or } i > s(\lambda) \end{cases} \tag{12}$$

The solution to the discrete problem, for given λ, is $o^*(\lambda) = \lfloor o^{c^*}(\lambda) \rfloor$.[33] Finally, the solution to the original district problem is given by $o^* = o^*(\lambda^*)$. The optimal Lagrange multiplier can be selected among a set of possible values, by comparing the values of the relaxed capacity constraint (i.e. the constraint associated to λ). The detailed procedure is outlined in Appendix E.

7.1.2 Teacher's Problem

Teacher have preferences over job characteristics. In each period, they receive a set of offers from school districts, and pick the one that maximizes their utility. I define the utility of teacher i from working in district j as v_{ij}. Teacher i also faces an outside option (denoted by 0), which gives her utility v_{i0}. Given a set of offers O_i, the problem of teacher i can therefore be expressed as follows:

$$\max_{k \in O_i \cup \{0\}} v_{ik} \tag{13}$$

As a result, the probability that teacher i accepts a job offer from district j can be written as $P(v_{ij} \geq \max\{\{v_{ik}\}_{k \in O_i \cup \{0\}})$.

7.2 Estimation

I estimate the parameters of teachers' utility and districts' payoffs. To do so, I make the following functional form assumptions. First, I assume that district j's payoff from hiring teacher i is linear,

[33] This solution method corresponds to the graphical solution to the knapsack problem provided by Dantzig (1957). All teachers are represented as points in a plane having utility net of λ on the vertical dimension and salary on the horizontal dimension. Each teacher has coordinates $(u_i - \lambda, w_i)$. The solution consists in rotating clockwise a ray with the origin as pivot point and the vertical axis as starting point, and in setting $o_i^*(\lambda) = 0$ for all teachers swept out by the ray, until the point in which the sum of their salaries exceeds the budget.

and equal to

$$u_{ij} = \beta_j x_i + \varepsilon_{ij} \tag{14}$$

The vector β_j contains the parameters to be estimated. The vector x_i includes teacher-specific covariates that enter districts' payoffs, such as a standardized measure of value-added, seniority (measured in years), and academic qualifications, i.e. a dummy for having a Master degree. The variable ε_{ij} is an idiosyncratic component, which I assume to be independent across teachers and districts, and identically normally distributed with mean μ_ε^2 and variance σ_ε^2. For simplicity, I assume that the parameters of the vector β_j relative to seniority, having a Master, and being an entrant are constant across districts.

I assume that the utility of teacher i from accepting district j's offer is a linear function of teacher-district characteristics, and equal to

$$v_{ij} = \alpha_z z_{ij} + \xi_{ij} \tag{15}$$

The vector α_z contains the parameters of the teacher utility I estimate. The vector z_{ij} includes district-specific as well as teacher-district-specific variables such as salary (in $1,000), distance from the district where teacher i is an incumbent (in miles), an indicator for teacher i being an incumbent in district j (which captures the cost of moving across districts, constant across teachers and districts), the share of economically disadvantaged students, and an indicator for j being an urban district. The variable ξ_{ij} is an idiosyncratic utility component, which I assume to be independent across districts, and identically distributed according to a Extreme Value type 1 distribution. I model teacher i's utility from the outside option as being constant in expectation across teachers, and equal to $v_{i0} = \alpha_0 + \xi_{i0}$, where ξ_{i0} is independent across teachers and from ξ_{ij}, and identically distributed according to a Extreme Value type 1 distribution. I denote the term $(\alpha_x z_{ij} - \alpha_0)$ as V_{ij}.

Each district's budget limit is constructed by applying the pre-Act 10 growth rate of total salaries to the previous year's wage bill. The capacity limit is obtained by multiplying total enrollment in the district by a fixed constant, equal to the average of the teacher-student ratio in place in each district until 2011.

Salaries

Estimation of teacher preferences requires observing the characteristics of all the job alternatives available to a teacher, including salaries. In the data, however, salaries are only observed when a match is realized. To construct salary counterfactuals for unrealized matches, I model salaries as being determined as in the post-Act 10 regime, i.e. as a function of seniority, academic qualifications, and teacher quality:

$$w_{ijt} = \gamma_j X_{it} + \delta_j f(q_i) \tag{16}$$

where X_{it} is a full set of interactions between two-years seniority dummies and education dummies, and q_i is value-added of teacher i. I specify the function f to be a standard logistic function, to avoid constructing extreme (i.e. unreasonably high or negative) levels of salaries for teachers with very high or very low value-added.[34] I estimate the salary parameters γ_j and δ_j via OLS using data on post-reform teacher-district matches, and use these estimates to back out the salary counterfactuals for each possible teacher-district match used to estimate the structural model.

Modeling salaries in this way implies that the salary schemes in each district are not endogenously determined within the model. In other words, I exclude the possibility that a district's decision on which salary scheme to adopt is dependent from other endogenous variables of the model, for example pre-Act 10 student test scores or the composition of the teaching workforce. Figure A8 shows no evidence of a correlation between the coefficients δ - which capture the salary component that depends on teacher quality - and pre-Act 10 shares of disadvantaged students (with a slope coefficient of 4.60 and a p-value of 0.29), average value-added of teachers (with a slope coefficient of 172.8 and a p-value of 0.66), and standardized average math test scores (with a slope coefficient of -0.821 and a p-value of 0.99).

7.2.1 Estimation Procedure

I estimate the parameter vectors α_z (teachers' utility), α_0 (teachers' outside option), and β (districts' payoff) using a maximum likelihood estimator. To do so I use data from 223 Wisconsin districts for the year 2012. For computational simplicity, I divide Wisconsin in twelve separate geographic labor markets, corresponding to the twelve Cooperative Educational Service Agencies (CESAs). For computational feasibility I exclude CESAs 1 and 2, including respectively the school districts of Milwaukee and Madison.[35] I consider each market as a separate one: Teachers can only move within CESAs, and districts can only make offers to teachers already working in their CESA. In 2012, about 60 percent of movements of teachers happened within a CESA.

The estimation procedure develops in the following steps (t denotes year).

1. I draw the idiosyncratic shocks ε^z_{ijt} for each teacher, district, and year, from a standard normal

[34] The standard logistic function has the form $f(x) = 1/(1 + e^{-x})$.

[35] CESAs providing services to Wisconsin schools, such as professional development for teachers, support staff, principals, and district leaders; cooperative purchasing to maximize available resources; sharing of special professionals to meet student needs. Each CESA works with schools and districts in a particular region of Wisconsin. CESAs have no taxing authority and they receive no state aid, and rely on the fees from service contracts with member districts, and from federal, state or other grants.

distribution. I set the initial values of the parameters to α_0 and β_{0j}.

2. For each district, teacher, and year I compute the district's payoff as $u_{ijt} = \beta_{0j} x_{it} + \mu_\varepsilon + \sigma_\varepsilon \varepsilon^z_{ijt}$.

3. For each district and teacher, I compute the probability that the offer is accepted (conditional on an offer being made), h_{ijt}, with an iterative procedure:

   (a) I initially set h_{ijt} as being the probability that teacher i accepts the offer of district j when *all* districts make her an offer. The distributional assumption on ξ_{ijt} allows to write this probability as $h^{start}_{ijt} = \exp\{V_{ijt}\}/(1 + \sum_{k\in J} \exp\{V_{ikt}\})$.

   (b) Given h^{start}_{ijt}, I solve each district's problem and derive their optimal set of offers, o^*_{jt}, and the consequent set of offers received by each teacher, O_{it}.

   (c) Given O_{it}, I re-estimate the probability that an offer is accepted, if one is made, as $h_{ijt} = \exp\{V_{ijt}\}/(1 + \sum_{k\in O_{it}} \exp\{V_{ikt}\})$.

   (d) I iterate the process until convergence.

4. Having determined u_{ijt}, h_{ijt}, and w_{ijt}, I solve each district's problem. In this way I obtain the optimal set of offers, o^*_{jt}, and the consequent set of offers received by each teacher, O_{it}.

5. I write the log-likelihood function as

$$l(\alpha_x, \alpha_0, \beta|\mathbf{z}, \mathbf{x}) = \sum_{i=1}^{N} \log h_{ij(it)t} = \sum_{i=1}^{N} \log \left[\frac{\exp\{V_{ijt}\}}{1 + \sum_{k\in O_i} \exp\{V_{ikt}\}} \right] \tag{17}$$

   where $j(it)$ denotes the district to which teacher i is matched in year t.

The log-likelihood is maximized using a Nelder-Mead simplex algorithm as described in Lagarias et al. (1998). [36]

7.3 Identification

The model allows a pretty transparent identification of the preference parameters of teachers' utility. Identification relies on cross-districts heterogeneity in district characteristics (such as location and student composition), and on the variation in salaries introduced by Act 10. Movements of teachers across districts allow to identify the parameter vector α_z of teachers' utility from teaching. To see this, consider the following example. Suppose teacher x is an incumbent in district A, receiving a wage w_A, and receives an offer from district B, located 5 miles from A and offering a wage w_B, with $w_B > w_A$, and an offer from district C, located 7 miles from A and offering a wage w_C, with

[36] Optimization is implemented using the package *fminsearch* in Matlab.

$w_C > w_B$. The choice of teacher x identifies the parameters of teachers' utility. For example, if she chooses C, this will imply that the taste for higher salaries offsets the distaste for larger distance, and will translate into a higher utility parameter on salaries and a lower parameter on distance. Similarly, exit of teachers will identify the value of the outside option. If, among the above options, teacher x decides to exit public schools, this will imply a higher valuation of the outside option and tanslate into a higher estimate for the parameter α_0.

Identification of teacher demand, i.e. of the parameters entering districts' payoff function, is slightly more subtle. The parameters β and σ_ε are identified out of variation in the optimal offer strategies across districts. Differences in such strategies stem from variation in budget and capacity constraints caused by the attrition of different types of teachers over time. The intuition behind the identification of the parameters of districts' payoff (β) can be better understood with the following example. Suppose that districts A and B are identical in terms of students, teachers, preferences for teacher characteristics, size, salary structure, and budget. Suppose further that both districts lose one teacher, and therefore have to fill one vacancy. If district A's exiting teacher has 30 years of experience but district B's teacher has only 1, and more experienced teachers are more expensive, then district A has much money "freed up" when the teachers exits compared with district **B**. Thus, district A has a larger budget to spend on the hire of a new teacher. How it spends its extra funds, compared with B, reveals how teacher attributes are valued. For example, if A decides to hire a high value-added teacher, this will imply that districts value quality, and will translate into a higher estimate for the district's payoff parameter on value-added. If, instead, A decides to hire a high-seniority teacher, this will lead to estimating a larger seniority parameter.

7.4 Parameter Estimates and Elasticities

Table 13 shows estimates and standard errors of the parameters of the model. Teachers receive positive utility from salary and dislike districts that are further away from the one where they are currently working. A positive estimate for the dummy for being an incumbent in the district indicates a utility premium in staying in the same district over time, which in turn shows that moving costs are relevant. Teachers prefer urban districts compared with suburban or rural districts, while the share of disadvantaged students does not seem to have a significant effect on utility (Table 13, column 1).

To interpret the magnitudes of these coefficients it is useful to compare the implied elasticities of the probability of moving to a district with respect to the district's characteristics. A one-percent higher salary (equivalent to \$540 at the mean) is associated with a 0.32 percent increase in the probability that a teacher is matched to the district (Table 13, columns 1-2). Moving costs (which correspond to the opposite of the estimated dummy for being an incumbent in the district) are equal to approximately 3 percent of salary (0.9608/0.3248), or $1,600. A ten-percent larger distance (equivalent to 1.7 miles at the mean) is associated with a 5.2 percent lower probability. A ten-percent higher share of poor students (equal to 3.7 percent at the mean) is associated with a 0.3 percent higher probability (Table 13, column 2). Lastly, the premium for teaching in an urban district is equal to approximately 0.8 percent of salary, or $432.[37]

Comparing these elasticities allows to assess the relevance of each one of these job characteristics for each teacher's decision on where to teach. In addition, it allows to calculate compensating differentials, i.e. increases in salary required to attract and retain teachers to districts with certain characteristics. For example, consider two identical districts that want to hire a teacher employed in another district. One of the two districts is 2 miles further from the teacher compared with the other district. The estimated elasticities of distance and salary imply that the district that is further away must offer the teacher a 16 percent larger salary (approximately $8,640) in order to attract her.[38] Similarly, if the two districts are at the same distance from the teacher, but one of them is in an urban area and another one in a rural area, the rural district must offer the teacher a 0.8 percent higher salary.[39]

Estimates of the parameters of districts' payoff imply that districts prefer higher value-added teachers, as well as higher-seniority and more educated teachers. In particular, districts are indifferent between a teacher who has one extra year of seniority or 0.02 standard deviations higher value-added (1.304/52.175, Table 13, column 3). Similarly, the district's valuation of a Master degree is equal to 0.2 percent of a standard deviation of value-added (10.972/52.175, Table 13, column 3).

7.5 Model Fit

To assess the within-sample fit of the model I compare a set of moments obtained simulating the model on data from 2012, used in estimation, with the same set of moments taken from the data. The moments I use are the share of teachers moving to a different district and the share of teachers exiting public schools, for all teachers and separately for teachers with positive and negative value-added. Columns 1 and 2 of Table 14 show the results of this exercise. The share of teachers moving to a different district (within the same CESA) implied by the model is 0.0062, whereas it is 0.0001 in the data. These shares are similar for teachers with positive and negative value-added in the model; in

[37]As a reference, Levy and Wadycki (1974) estimate a distance elasticity of -0.43 and an income elasticity of 1.9 analyzing migration patterns of a sample of Venezuelan workers.

[38]Since a 1.7 miles larger distance (10 percent of the mean) is associated with a 5.2 percent lower probability of moving, and a $5,400 higher salary (10 percent of the mean) is associated with a 0.32 percent higher probability, the result follows.

[39]Defining p_{ij} as the probability that teacher i moves to district j, the elasticity of p_{ij} to a job characteristic z_{ij} implied by the logit assumption on the error term of teachers' utility is $\beta_z(1-p_{ij})z_{ij}$. The elasticities shown in the table are calculated at the mean of p_{ij} and z_{ij}.

the data, the moving rate is higher for teachers with lower value-added. The model implies a share of teachers exiting public schools equal to 0.0623; in the data, this share is 0.0620. For teachers with positive value-added this share is equal to 0.0637 as implied by the model, and 0.0750 in the data. For teachers with negative value-added this share is 0.0641 as implied by the model, and 0.0645 in the data. These figures indicate that, while the model predicts a lower moving rate than the one implied by the data, it performs very accurately in predicting exit rates.

To assess the extent to which the model is accurate in making out-of-sample predictions, I use data from 2009, which preceeds Act 10 and is therefore not used in estimation, to simulate the same moments and compare them with the moments observed in the data (Todd and Wolpin, 2006). I compute teacher salaries using the pre-reform regime, i.e. setting δ_{ij} equal to zero. The results from this exercise are shown in columns 3 and 4 of Table 14. The share of teachers moving to a different district implied by the model is 0.00009, whereas it is 0.0044 in the data. The model implies that 0.0634 of teachers exit public schools; in the data, this share is 0.0314. These results show that the model is not very accurate in predicting exit out-of-sample. This can be explained by considering that part of the large exit rates of Wisconsin teachers after Act 10 is attributable to a reform of public employees' pension contributions, which in practice changed older teachers' outside option. By assuming a fixed outside option value across teachers, the model is not able to incorporate this pattern, and therefore generates higher-than-observed exit rates when simulated on pre-Act 10 data.

8 Alternative Salary Schemes and The Allocation and Retention of Teachers

The structure provided by the model, along with estimates of the parameters, can be used to simulate the effects of alternative salary schemes on the composition of the teaching workforce. I focus on two types of counterfactuals. The first is a change in the component of salaries associated with value-added in one district (i.e. in δ), with salaries unchanged in all other districts. The second is an equal change in δ in all districts at the same time. In both cases I assume that the change is budget-neutral. This implies a redistribution of salaries from low value-added to high value-added teachers.

8.1 Increase in Quality Pay in One District

I start by studying the effect of a change in δ in one district only. In a world in which districts have identical preferences and select a salary structure based on idiosyncratic preferences of superintendents and school boards, such change would be consistent with, for example, a change of the composition of the school board in one district but not in others. In a world in which districts have heterogeneous preferences over teachers or heterogeneous valuations of teachers' characteristics, this counterfactual could be rationalized with a change in preferences or valuations in one district but not in all the others.

When δ varies, it affects both the supply and demand of teachers. A change in salaries modifies the budget constraint of the district affected by the policy, and in turn the problem that the district faces. In equilibrium the district could therefore make a different set of offers compared with the status-quo. Similarly, a change in salaries affects the utility that teachers derive from working in the district. This will change the preference ordering of districts for the point of view of each teacher, and in turn be the probability that a teacher gets matched with *any* district - not only the one affected by the policy. To incorporate these effects in the counterfactual analysis, I solve all districts's problem and derive the probabilities of each possible match for 5 possible values of δ, ranging from 0 to \$4,000 (approximately one standard deviation of the estimate of the parameters in the subsample of individual-salary districts, Figure A5).

In order to keep a balanced budget, I assume that base salaries adjust immediately depending on the new value of δ and the current composition of the teaching workforce in the district. As explained in the previous section, the salary of teacher i when employed in district j is equal to $w_{ij} = \gamma_{0j} + \gamma_{xj}\hat{X}_i + \delta_j VA_i + \omega_{ij}$.[40] In this specification, the coefficient γ_{0j} represents the base salary in district j. Denoting the set of teachers employed in district j as T_j, the adjusted level of salaries corresponding to a new merit component of salaries $\tilde{\delta}_j$ is equal to $\tilde{\gamma}_{0j} = \gamma_{0j} + (\tilde{\delta}_j - \delta_j)\sum_{i \in T_j} VA_i$. I let δ range from \$0 to \$8,000, and analyze the change in the probability that teachers in different quartiles of the value-added distribution move to, move out of, or exit from a district, as well as the change in the composition of movers to the districts, movers out of the districts, exiters, and the whole teaching body of the district.

For expositional purposes it is useful to discuss the effects of this counterfactual policy on one district at the time. For expositional purposes I focus here on the effects of changes in δ on teacher movements and on the composition of the teaching workforce for the Chippewa Falls Area school district, situated in the central-western area of the State, in the county of Chippewa and in the Chippewa-Eau Claire metropolitan area. This suburban district, running 5 elementary schools, one middle school, and two high schools, enrolled 5,027 students in 2012, of which 38 percent were economically disadvantaged, and employed 303 teachers in my sample. With these characteristics, the

[40]Note that $\gamma = [\gamma_0, \gamma_x]$ and $X_i = [1, \hat{X}_i]$.

district, classified as salary-schedule, is an example of the "average" Wisconsin district.

Figure 9 shows the simulated probability that a teacher moves to, moves out of, or exits the district, separately for different quartiles of value-added. The parameter δ is equal to \$116 after 2011. The simulated probability that teachers move to the district declines by 37.8 percent when δ equals \$4,000, compared to when it is equal to zero, for teachers with value-added in the bottom quartile, whereas it increases by 42.9 percent for those with value-added in the top quartile (Figure 9, left panel). The simulated probability that teachers move out to the district increases by 5.0 percent when δ equals \$4,000 compared to when it is equal to zero for teachers with value-added in the first quartile, whereas it declines by 12.3 percent for those with value-added in the fourth quartile (Figure 9, center panel). Lastly, the probability that teachers exit the district increases by 1.25 percent when δ equals \$4,000, compared to when it is equal to zero, for teachers with value-added in the bottom quartile, and it declines by 1.29 percent for those with value-added in the top quartile (Figure 9, right panel).

Figure 10 shows the simulated average value-added of teachers moving in, out, and exiting the school district for different values of δ, and the overall composition of the district's teaching workforce. In 2012, average value-added of teachers working in the district is equal to -0.0797. The figure shows that the composition of movers out of the districts and exiters becomes worse (i.e. average value-added declines) as δ grows. In particular, average value-added of movers to the district increases by 1.5 times when δ equals to \$4,000 compared with the case in which δ equals zero, whereas average value-added of movers out of the district declines by 13 times, and average value-added of exiters declines by 15 percent. As a result, the overall composition of the district improves by 1.3 percent when $\delta = \$4,000$ (Figure 10).

The results of this counterfactual analysis indicate that an increase in the quality component of salaries in only one district is associated with an improvement in the composition of the district's teaching workforce. This improvement is driven by higher-value-added teachers moving to the district from other districts, induced by a potential increase in their salaries, and by lower-value-added teachers moving out of the district or exiting public schools, discouraged by a possible decrease in their salary.

8.2 Introduction of Quality Pay in All Districts

I now simulate the effect of an increase in quality pay in *all* districts at once on the composition of the teaching workforce in different types of districts. In a context in which districts have identical preferences, this counterfactual scenario could be rationalized with superintendents and school boards becoming aware of the necessity to reward teachers for their quality. In addition, it could be seen as the scenario that would naturally arise if districts started poaching teachers from each other.

It should be pointed out that the results from this second counterfactual exercise do not trivially follow from the first. This can be seen considering the decision of a teacher in each period. She must decide whether to stay where she is, move to another district, or exit teaching. The second counterfactual changes two out of three options and, for this reason, changes the value of exiting relative to remaining in public schools compared with the first counterfactual. As a result, the effects of such change in salaries on the exit behavior of teachers could in principle be very different from the one outlined in the previous subsection.

Figure 11 shows the simulated probability that a teacher moves to, moves out of, or exits the district, separately for different quartiles of value-added. The simulated probability that teachers move to the district declines by 71 percent when δ equals \$4,000, compared to when it is equal to zero, for teachers with value-added in the bottom quartile, whereas it increases by 68 percent for those with value-added in the top quartile (Figure 11, left panel). The simulated probability that teachers move out to the district declines by 68 percent for teachers in the bottom quartile, and it increases by 39 percent for teachers with value-added in the top quartile (Figure 11, center panel). Lastly, the probability that teachers exit the district increases by 1.26 percent when δ equals \$4,000, compared to when it is equal to zero, for teachers with value-added in the bottom quartile, and it declines by 1.3 percent for those with value-added in the top quartile (Figure 11, right panel).

Figure 12 shows the simulated average value-added of teachers moving in, out, and exiting the school district for different values of δ, and the overall composition of the district's teaching workforce. The figure shows that the composition of exiters becomes worse (i.e. average value-added declines) as δ grows. In particular, average value-added of exiters to the district declines by 15 percent when δ equals to \$4,000 compared with the case in which δ equals zero. Average value-added of movers out of the district, however, increases by more than 30 times. Lastly, average value-added of movers to the district increases by almost 4 times. As a result, the overall composition of the district improves by 1.1 percent when $\delta = \$4,000$ (Figure 12).

The results of this counterfactual analysis indicate that an increase in the quality component of salaries in all districts at the same time is associated with a slightly smaller improvement in the composition of a district's teaching workforce compared with the one associated with a one-district increase in δ. This happens because, in the case of a one-district increase, part of the improvement is driven by better teachers moving into the district, and worse teachers moving out of the district. The net inflow of higher-quality teachers is totally offset when δ increases in all districts, because teacher quality is rewarded at the same rate everywhere: in the case of Chippewa Falls, we observe higher-quality teachers moving to the district, but also out of the district.

Results from the two counterfactuals suggests that the observed improvement in the composition of the teaching workforce in individual-salary districts, as well as the achievement gains experienced by students in these districts, might be a short-run effect of Act 10. If in the future all districts move towards merit pay, in an attempt of attracting and retaining the best teachers, the longer-term effects of Act 10 in each district and in the whole state might be more limited in size.

In interpreting the outcomes of these counterfactual policies, however, one caveat applies: These simulations do not incorporate entry. If the entry behavior of new teachers mirrors their exit behavior, in both scenarios we would observe an increase in average quality of entrants, which could translate into a larger improvement in the composition of the teaching workforce than the one observed in the simulations.[41] The decision of entering teaching is, however, likely to be very different from the one of exiting. For this reason, a thorough analysis of the effects of changes in the salary structure on the supply of teachers is left to future research. The results of the counterfactuals presented above only inform us on the contribution of changes in mobility and exit to changes to the composition of the workforce, and could be interpreted as the scenario that would arise if the average quality of the new teachers simply remained constant and equal to the average quality of all other teachers.

9 Conclusion

This paper has studied the effects of a reduction in the scope of collective bargaining over teacher salaries on the composition of the teaching workforce and, in turn, on student achievement. To study this question I have exploited a recent reform of collective bargaining in Wisconsin, known as Act 10 and passed in 2011. This Act, which prohibits collective bargaining over seniority-based salary schedules of public sector employees, has given school districts freedom to set teacher salaries on an individual basis.

Evidence based on teacher-level data shows that teachers responded to salary changes by moving across districts and by leaving public schools. In particular higher-quality teachers moved from salary-schedule districts to individual-salary districts, whereas lower-quality teachers exited from individual-salary districts. These sorting patterns lead to a small increase in average quality of the teaching workforce in individual-salary districts. These districts also experienced a sizeable 6 percent gain in achievement after 2011 compared with salary-schedule districts, only in part attributable to an

[41] Hoxby and Leigh (2004) show that the increase in wage compression that has accompanied the rise in unionization of public schools explains the largest part of the decline in entry of high-performing teachers observed in the US since 1960. Rothstein (2014) demonstrates that higher salaries and lower tenure rates can improve the supply of new teachers. Dolton (1990) emphasizes the importance of relative earnings and earnings growth in the decision to become a teacher.

improvement in the composition of the teaching workforce.

To provide a better understanding of how teachers decide whether and where to teach, I build and estimate a two-sided model of the teacher labor market, to disentangle demand and supply forces at play in driving the sorting patterns observed in the data. Estimates of the supply side of the model show that, on average, a 10 percent increase in salaries in one district increases the probability that a teacher would move to that district by 3 percent. In addition, distance and a higher percentage of disadvantaged students discourage teachers from moving to a district. Estimates of teacher demand show that districts prefer less experienced and higher quality teachers. Estimates of this model can be used to inform several education policies, for example those aimed at addressing issues of selection and retention of high-quality teachers, at the forefront of the public attention in the last years.

I use the model to simulate the effects of alternative salary schemes on the composition of the teaching workforce. Results from these simulations show that an increase in the merit pay component of salaries in one district is associated with an increase in average quality of the district's teaching workforce, driven by an inflow of higher-quality teachers from other districts and an outflow of lower-quality teachers to other districts or out of the profession. When the same salary change affects all districts at once, the composition of the workforce improves by a smaller extent. Results from this second counterfactual exercise suggest that the observed improvement in the composition of the teaching workforce in individual-salary districts, as well as the achievement gains experienced by students in these districts, might be short-lived, and that the longer-term compositional change in each district and in the state as a whole might be smaller. This counterfactual, however, does not take into account potential long-run changes in the supply of new teachers; its implications should therefore be interpreted with caution.

The debate on the role of teacher unions, and on the consequent changes in the characteristics of a teaching job, are currently at the forefront of the political debate (*Friedrichs v. California Teachers Association* is just one of the many court cases on the topic). Given the fundamental role that individual teachers play in shaping children's educational opportunities (Rockoff, 2004), understanding the effect that these changes have on the composition of the teaching workforce is fundamental to correctly assess the outcomes of policies shaping unions' powers from the perspective of student achievement growth. This paper provides a useful assessment of these effects, exploiting a recent policy change that has currently affected one US state, but that is likely to be replicated in similar forms in other states. While this paper has focused on movements of teachers across districts and exit from the profession, the effects of a policy such as Act 10 on entry in the teaching profession remain unstudied. As pointed out by Rothstein (2014), these effects, likely to manifest in the next few years, are an equally interesting and policy-relevant, and represents an avenue for future research.

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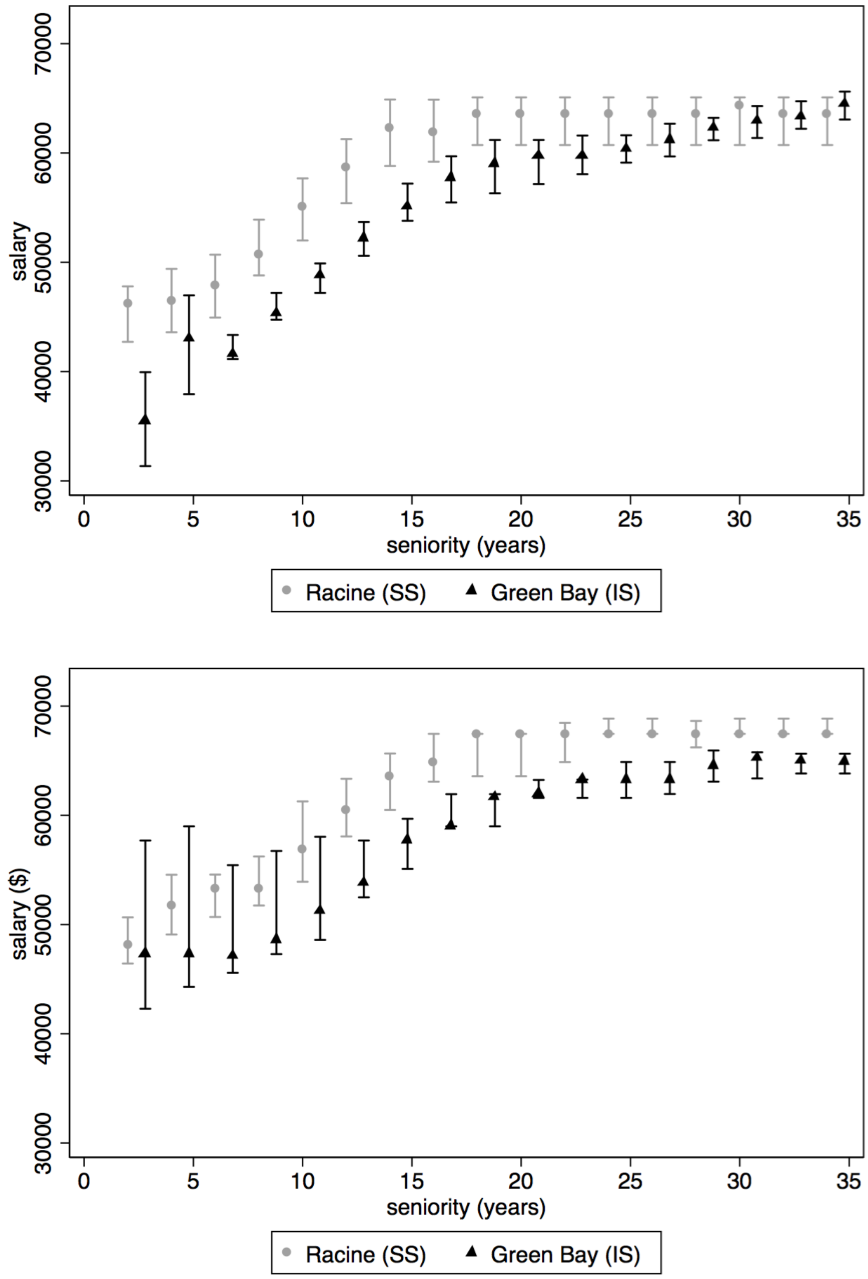
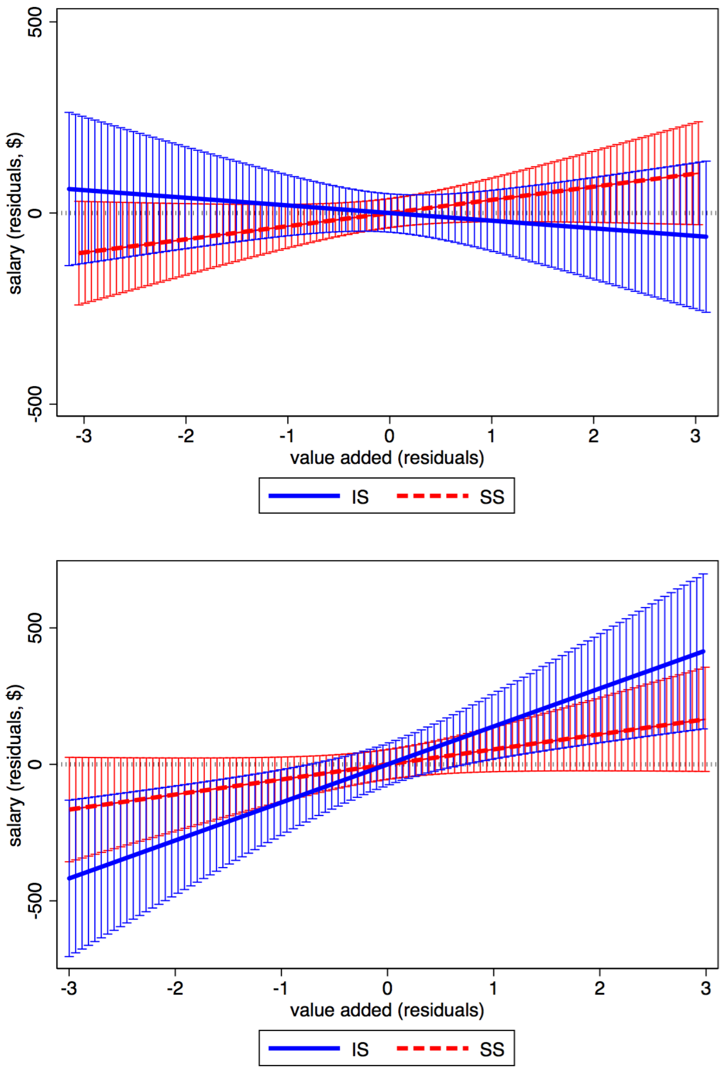
Figures

Figure 1: Empirical salary schedule - Median and interquartile range of salaries, years 2007-2011 (top) and 2012-2014 (bottom)



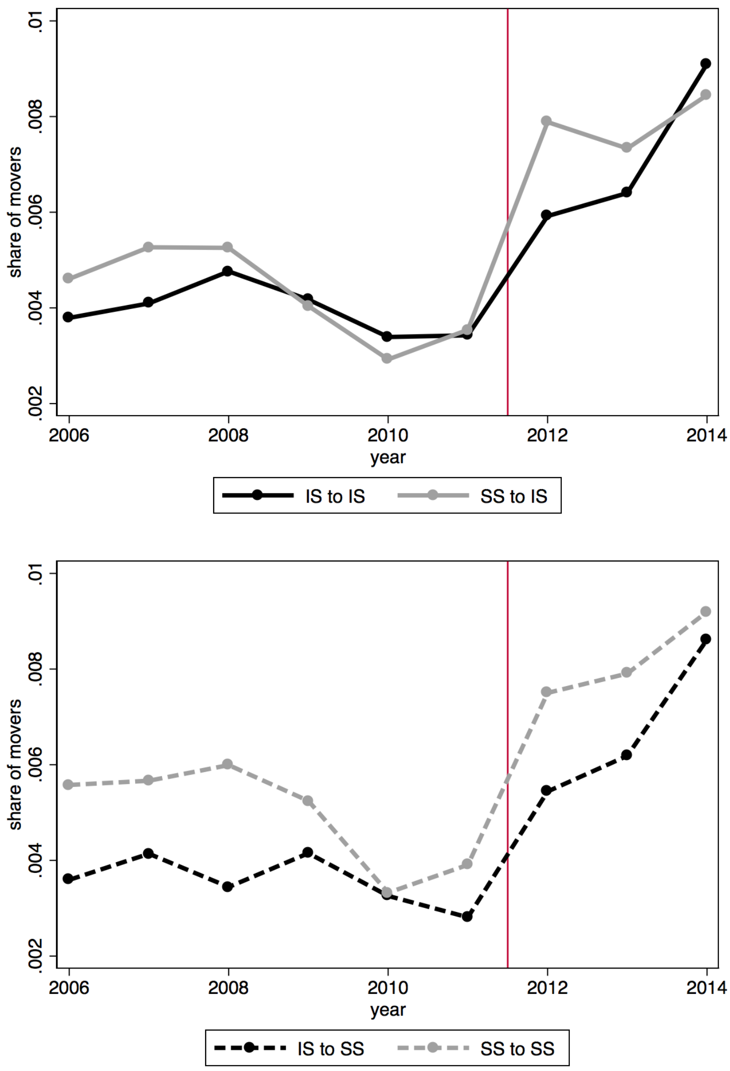
Notes: Median and interquartile range of salaries, by two-years seniority classes, for the Racine School District (grey) and the Green Bay Area School district (black). The sample is restricted to teachers having less than 35 years of experience and holding a Master degree.

Figure 2: Correlation, salaries and value-added residuals: 2007-2011 (top panel) and 2012-2014 (bottom panel)



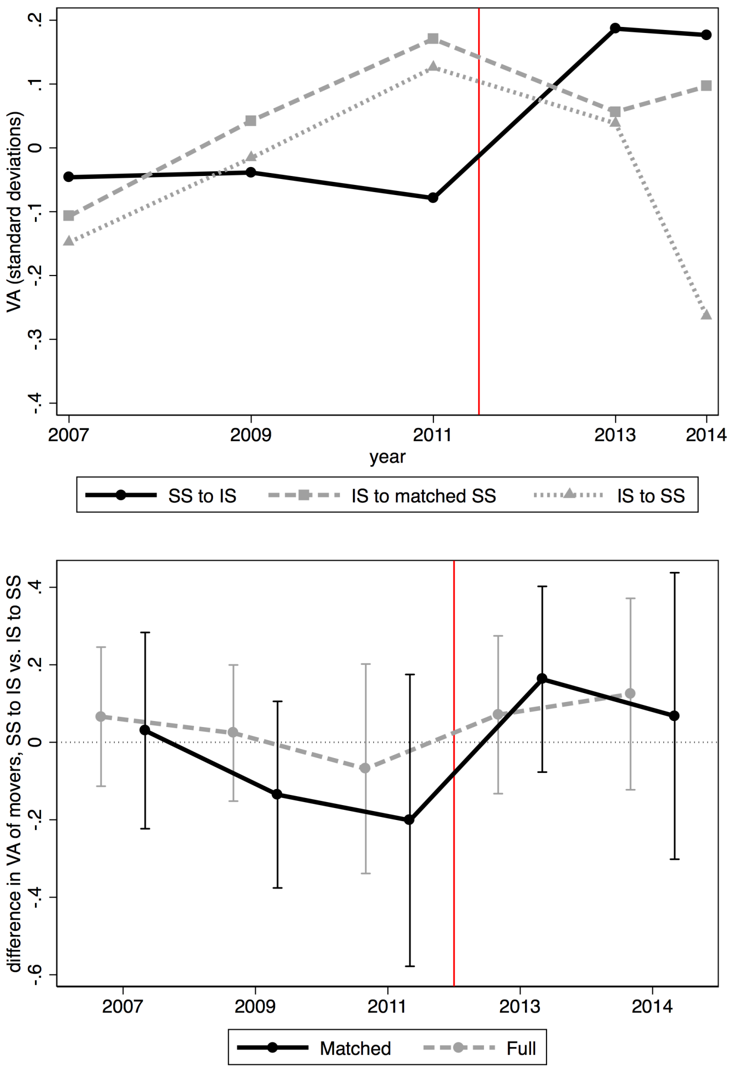
Notes: Linear fit lines of salary residuals (vertical axis) and teacher value-added residuals (horizontal axis). The shaded areas are 95-percent confidence intervals of the linear fit lines. Salary and value-added residuals are obtained from a regression on a full set of interactions between education (Bachelor, Master, Ph.D.) and two-years seniority dummies, and year fixed effects, and estimated separately for each district and for the periods 2007-2011 and 2012-2014. Teachers with value-added smaller than -3 standard deviations and larger than 3 standard deviations (less than 1 percent of the sample) are excluded. The sample is restricted to 110 individual-salary and 122 salary-schedule districts with information on post-2011 handbooks, enrolling 83 percent of the total student population.

Figure 3: Share of teachers moving across public school districts, by type of district of origin and destination



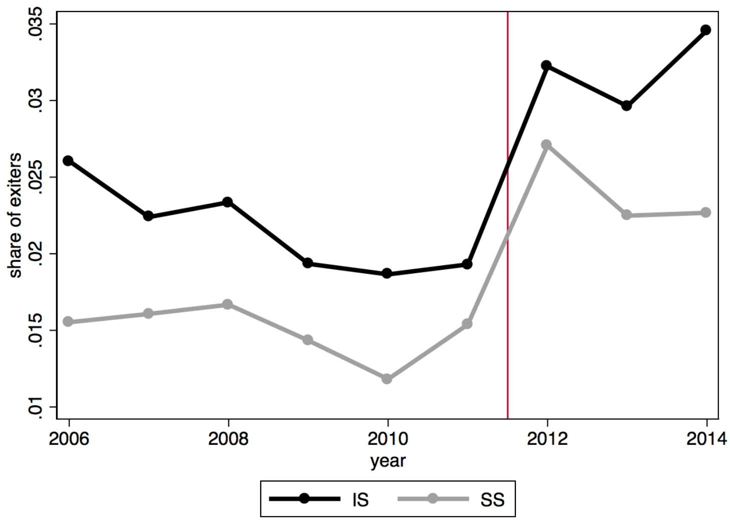
Notes: Share of teachers changing district in each year, by type of district of origin and destination. Each share is defined as the total number of movers, divided by the total number of teachers employed in Wisconsin public schools in each year in 223 districts with non-missing handbook information. The individual-salary subsample includes 101 districts, the salary-schedule subsample includes 122 districts. The subsample covers 83 percent of the total student population.

Figure 4: Average value-added of teachers moving across districts (top panel) and Difference in value-added of movers, SS to IS vs. IS to SS



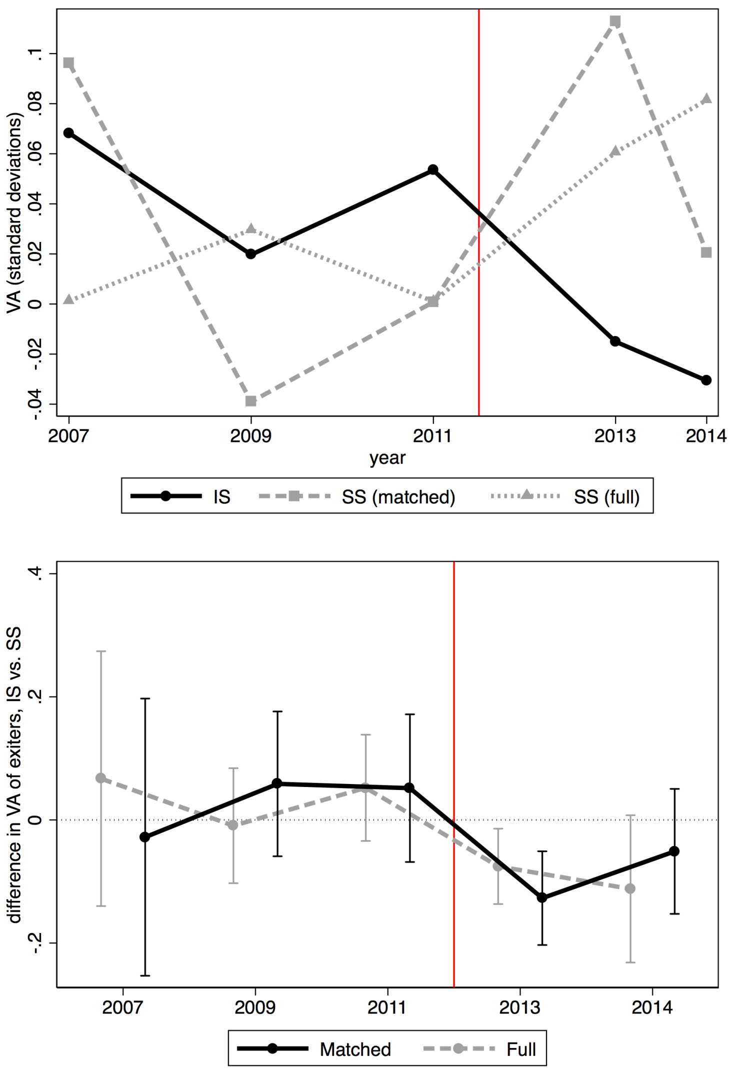
Notes: Top panel: Average value-added of teachers moving across Wisconsin districts between 2006 and 2014, by type of district of origin and destination. Bottom panel: OLS point estimates and confidence intervals of the coefficients β_t in the regression $q^m_{jt} = \sum_{s=2006}^{2014} \beta_s IS_j * \theta_s + \theta_t + \varepsilon_{jt}$, where q^m_{jt} is average value-added of teachers moving to district j in time t, IS_j equals 1 for individual-salary districts, and τ_t is a vector of two-year dummies. Standard errors are clustered at the district level. The sample is restricted to teachers moving either from salary-schedule to individual-salary districts, or from individual-salary to salary-schedule districts. The individual-salary subsample includes 101 districts, the matched salary-schedule subsample includes 64 districts, the full salary-schedule subsample includes 122 districts. The matched sample is obtained using nearest-neighbor Mahalanobis matching on observable characteristics of the school districts.

Figure 5: Share of teachers exiting public schools



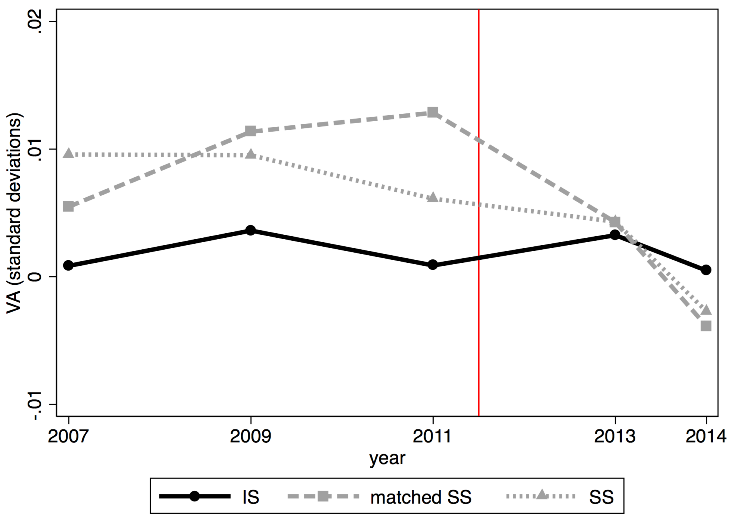
Notes: Share of teachers exiting public schools from the two types of districts over time. Each share is defined as the total number of teachers exiting from each type of district, divided by the total number of teachers employed in Wisconsin public schools in each year. The individual-salary subsample includes 101 districts, the salary-schedule subsample includes 122 districts.

Figure 6: Top panel: Average value-added of teachers exiting Wisconsin public schools. Bottom panel: Difference in value-added of exiters, SS vs. IS



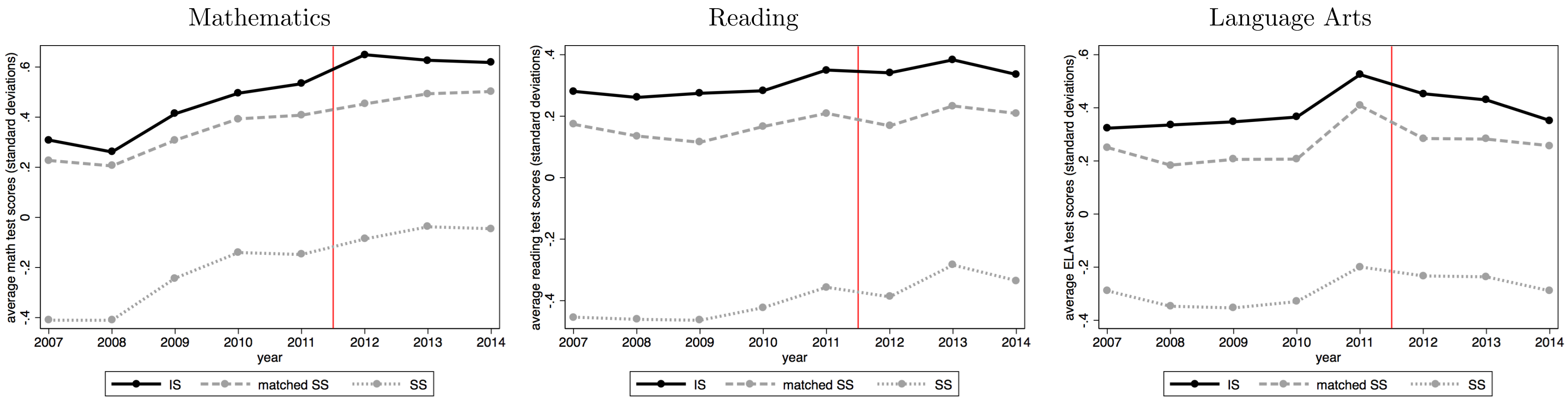
Notes: Top panel: Average value-added of teachers exiting public schools in Wisconsin between 2006 and 2014, by type of district of origin. Bottom panel: OLS point estimates and confidence intervals of the coefficients β_t in the regression $q^e_{jt} = \sum_{s=2006}^{2014} \beta_s IS_j * \theta_s + \theta_t + \varepsilon_{jt}$, where q^e_{jt} is average value-added of teachers exiting district j in time t, IS_j equals 1 for individual-salary districts, and τ_t is a vector of two-year dummies. Standard errors are clustered at the district level. The individual-salary subsample includes 101 districts, the matched salary-schedule subsample includes 64 districts, the full salary-schedule subsample includes 122 districts. The matched sample is obtained using nearest-neighbor Mahalanobis matching on observable characteristics of the school districts.

Figure 7: Average value-added of teachers in Wisconsin public schools



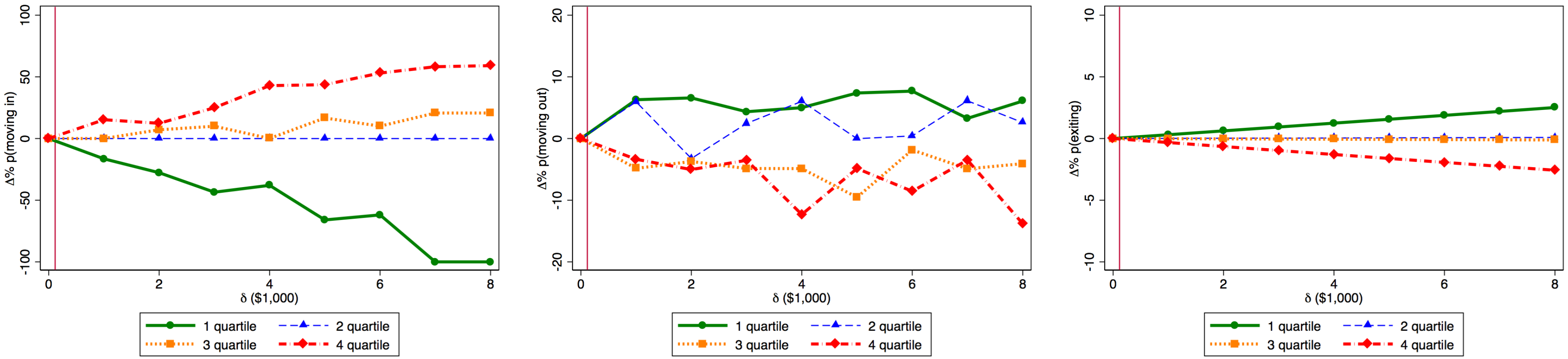
Notes: Average value-added of teachers employed in public schools in Wisconsin between 2006 and 2014, by type of district. The individual-salary subsample includes 101 districts, the matched salary-schedule subsample includes 64 districts, the full salary-schedule subsample includes 122 districts. The matched sample is obtained using nearest-neighbor matching on observable characteristics of the school districts.

Figure 8: Average standardized test scores



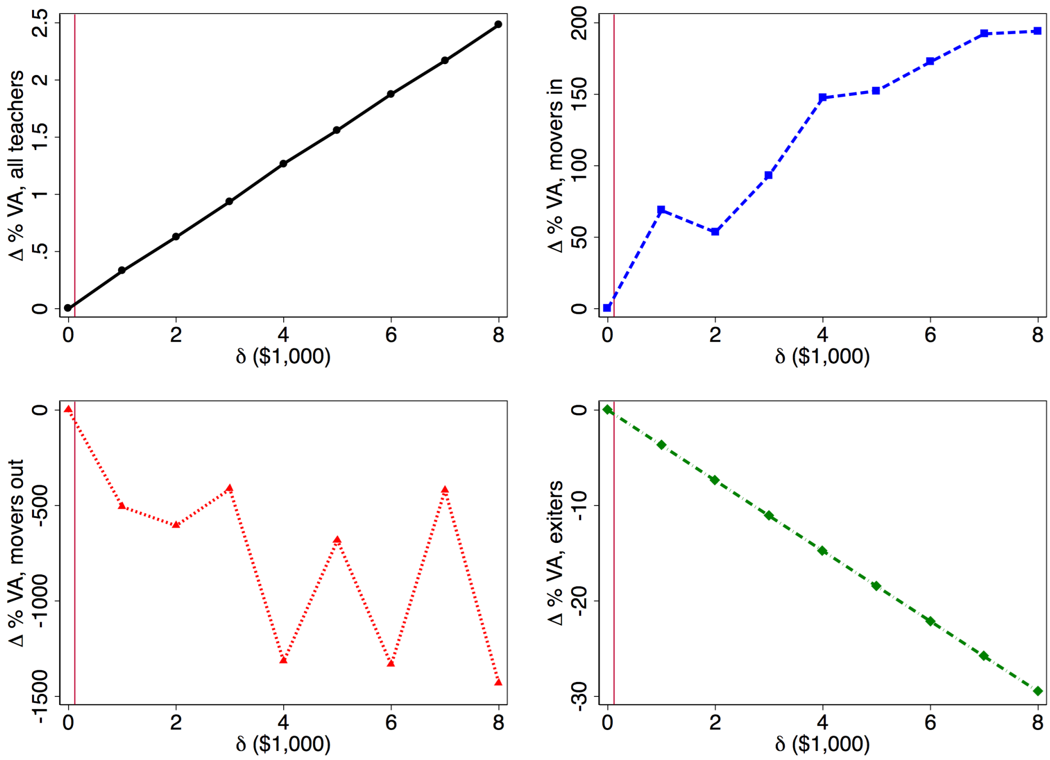
Notes: Average standardized test scores at the grade-school-subject level over time, separately for mathematics, reading, and language arts. Test scores are standardized within each grade-subject level using the 2007 state distribution of test scores. The individual-salary subsample includes 101 districts. The full salary-schedule subsample includes 122 districts. The matched salary-schedule subsample includes 64 districts. The matched sample is obtained using nearest-neighbor Mahalanobis matching on observable characteristics of the school districts.

Figure 9: Counterfactual 1 - Teacher responses to an increase in δ in Chippewa Falls school district: % change in the probability of moving in (left panel), moving out (middle panel), and exiting (right panel)



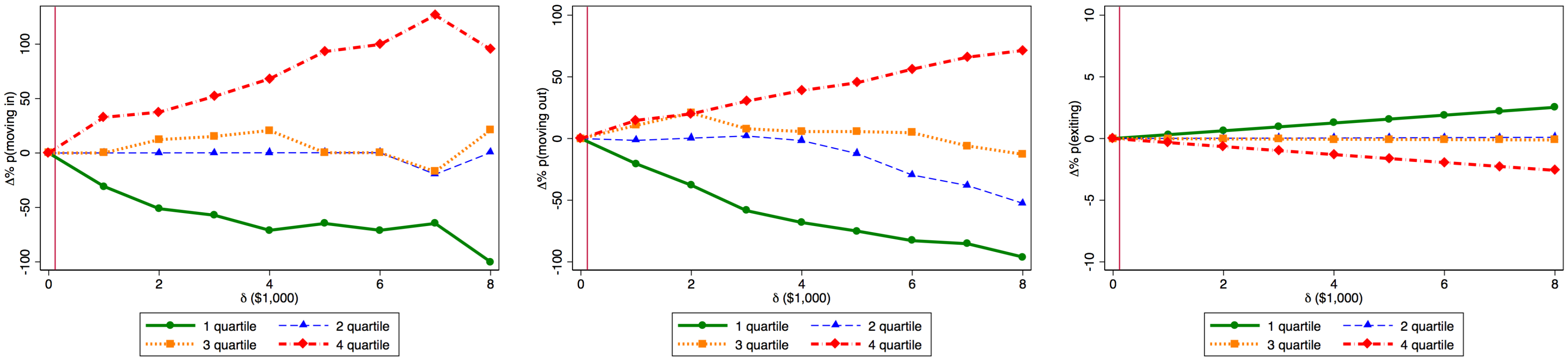
Notes: Percentage change in the probability of of moving to the Chippewa Falls school district district (left), out of the district (center) and out of public schools from the district (right), for teachers in different quartiles of the distribution of value-added, associated with changes in δ (as defined in equation 16) limited to the district.

Figure 10: Counterfactual 1 - Compositional changes, Chippewa Falls school district



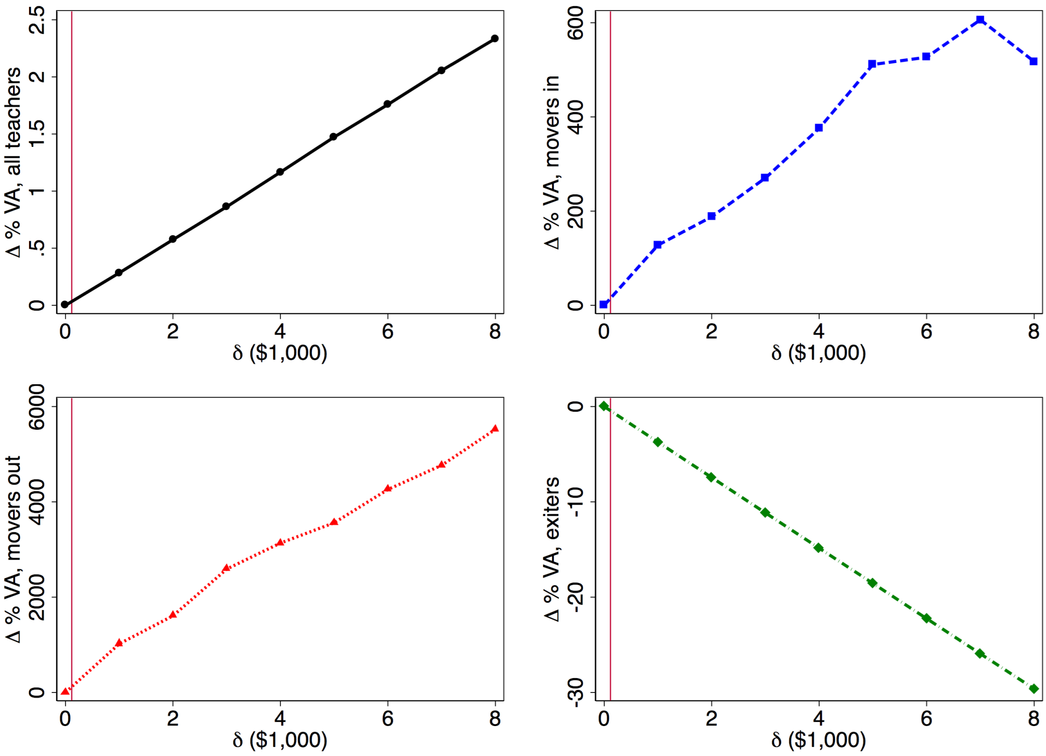
Notes: Percentage change in average value-added of teachers moving to the school district of Chippewa Falls, out of the district, exiting public schools from the district, and average value-added of teachers working in the district, associated with changes in δ (as defined in equation 16) only in the school district of Chippewa Falls.

Figure 11: Counterfactual 2 - Teacher responses to an increase in δ in all districts, for the Chippewa Falls school district: % change in the probability of moving in (left panel), moving out (middle panel), and exiting (right panel)



Notes: Percentage change in the probability of of moving to Chippewa Falls school district district (left), out of the district (center) and out of public schools from the district (right), for teachers in different quartiles of the distribution of value-added, associated with changes in δ (as defined in equation 16) in all districts.

Figure 12: Counterfactual 2 - Compositional changes, Chippewa Falls school district



Notes: Percentage change in average value-added of teachers moving to the school district of Chippewa Falls, out of the district, exiting public schools from the district, and average value-added of teachers working in the district, associated with changes in δ (as defined in equation 16) in all districts.

Tables

Table 1: Summary statistics - teachers

	pre-2011	post-2011	Total
Female	0.731	0.743	0.734
	(0.443)	(0.437)	(0.442)
Experience	14.88	14.47	14.78
	(9.613)	(8.843)	(9.437)
has B.A.	0.485	0.439	0.474
	(0.500)	(0.496)	(0.499)
has Master's	0.509	0.553	0.520
	(0.500)	(0.497)	(0.500)
has Ph.D.	0.002	0.002	0.002
	(0.042)	(0.042)	(0.042)
Salary ($)	50,620	53,693	51,351
	(10,965)	(11,406)	(11,149)
Mover	0.022	0.035	0.025
	(0.146)	(0.183)	(0.156)
Exiter	0.038	0.052	0.041
	(0.191)	(0.221)	(0.198)
N. of teachers	78,307	66,849	92,342

Note: Teacher data from the PI-1202 Fall Staff Report - All Staff Files for the academic years 2005-2006 to 2013-2014, published by the Wisconsin Department of Public Instruction (WDPI). The sample is restricted to non-substitute teachers working in 422 Wisconsin public school districts. Teachers earning top 1% and bottom 1% of FTE-adjusted salaries are excluded from the sample. Teachers working in the Kenosha School District are excluded due to mistakes in salary data. Salaries are expressed in full-time equivalents. Years of seniority are adjusted using the procedure described in Appendix B.

Table 2: individual-salary and salary-schedule districts: pre-Act 10 characteristics

	IS	SS	Difference IS - SS	SS (matched)	Difference IS - SS matched
	(1)	(2)	(3)	(4)	(5)
urban	0.0594	0.0738	-0.0144	0.0781	-0.0187
	(0.237)	(0.262)	(0.0195)	(0.269)	(0.0195)
suburban	0.297	0.197	0.100***	0.219	0.0783*
	(0.458)	(0.398)	(0.0331)	(0.414)	(0.0407)
property value per pupil	831146.8	616590.4	214556.4***	605,523	225624***
	(997650.0)	(403729.3)	(57067.1)	(418,834)	(75,934)
enrollment	2926.1	3055.1	-129.0	2818.5	107.6
	(3034.3)	(6789.8)	(421.1)	(3675.4)	(304.2)
% black students	2.876	3.179	-0.303	3.192	-0.317
	(4.595)	(7.197)	(0.486)	(6.396)	(0.506)
% disadvantaged students	32.85	36.61	-3.908***	35.69	-3.230**
	(14.38)	(14.98)	(1.141)	(14.40)	(1.326)
math test scores	476.1	472.2	3.930***	473.9	2.159*
	(12.38)	(12.51)	(0.984)	(11.43)	(1.128)
reading test scores	478.9	475.6	3.338***	476.7	2.260**
	(9.773)	(9.150)	(0.745)	(8.650)	(0.878)
experience	13.83	14.44	-0.614***	14.52	-0.577***
	(1.865)	(1.968)	(0.149)	(2.055)	(0.179)
Bachelor	0.453	0.484	-0.0312***	0.468	0.0147
	(0.136)	(0.144)	(0.0109)	(0.128)	(0.0123)
Master	0.542	0.512	0.0299***	0.527	0.0147
	(0.135)	(0.146)	(0.0109)	(0.131)	(0.0123)
Ph.D.	0.00149	0.000890	0.000605**	0.0013	0.0002
	(0.00423)	(0.00286)	(0.000275)	(0.0036)	(0.0004)
VA	0.007	0.008	-0.001	0.0429	-0.0363
	(0.290)	(0.224)	(0.0200)	(0.222)	(0.0246)
salary ($)	52459.8	50421.6	2050.2***	51281.2	1231.1**
	(5406.0)	(4841.2)	(396.4)	(4880.6)	(480.6)
salary, experience$\leq$5 ($)	38970.3	37896.6	1073.7***	38006.8	827.5**
	(3806.9)	(3370.6)	(277.8)	(3159.7)	(327.3)
salary, experience>20 ($)	62371.9	59665.2	2736.7***	60906.2	1518.2**
	(6789.7)	(6578.1)	(519.1)	(7153.2)	(640.4)
N. of districts	101	122		64	

Note: Means and standard deviations (in parentheses) of district-level characteristics of individual-salary districts, salary-schedule districts, and matched salary-schedule districts (columns 1 2, and 4), and differences between individual-salary and salary-schedule districts (column 3) and between individual-salary and matched salary-schedule districts (column 5). The individual-salary subsample includes 101 districts, the salary-schedule subsample includes 122 districts. The subsample covers 83 percent of the total student population. The matched sample of salary-schedule districts is obtained via nearest-neighbor Mahalanobis matching, and contains 64 districts.

Table 3: Interquantile regressions - Dependent variable is residual of ln(salary)

	25-75				50-75			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS	0.004***	0.009***	-0.001	0.007***	0.004***	0.008***	-0.000	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
post 2011	0.004***	0.005***	0.004*	0.005***	-0.001***	-0.001	0.000	-0.001*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)
IS * post 2011	0.002**	0.003***	0.005	-0.002	0.004***	0.003***	0.004*	0.001*
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Sample	All	Master	Master, < 10	10+	All	Master	Master, < 10	10+
Observations	321041	188930	44182	214667	321041	188930	44182	214667

Note: The dependent variable is the natural logaritm of salaries. Each regression tests the effects of the variables on interquantile ranges of the distribution of the dependent variable, controlling for two-years seniority dummies, education dummies, and district fixed effects. The sample is restricted to the 223 districts in Wisconsin with nonmissing contract data, covering 83 percent of the total student population.

Table 4: OLS - Dependent variable is salary residuals

	All districts	IS	SS	All districts
	(1)	(2)	(3)	(4)
VA	26.259	-19.983	34.401	34.401
	(30.8922)	(63.4252)	(41.8090)	(41.7305)
VA * post	44.150	158.636**	20.279	20.279
	(34.4606)	(75.0364)	(36.8360)	(36.7669)
IS				-0.000
				(0.0000)
VA * IS				-54.384
				(75.7789)
IS * post				-0.000
				(0.0000)
VA * IS * post				138.357*
				(83.3776)
Observations	117364	40819	54666	95485

Note: The dependent variable is residual salary, the variable *VA* is residual value-added. The variable *IS* equals 1 for 101 districts classified as individual-salary. The control group are 112 districts classified as salary-schedule. The variable *post* equals 1 for years following 2011. Residuals are obtained from a regression of these variables on two-years seniority dummies interacted with education dummies, year fixed effects, and district fixed effects, estimated separately for the years 2007-2011 and 2012-2014. Standard errors are clustered at the district level.

Table 5: OLS - Dependent variable is value-added of movers across districts

	(1)	(2)	(3)	(4)
IS	-0.0178	-0.1370	0.0557	-0.0213
	(0.0816)	(0.1000)	(0.0585)	(0.0748)
IS * post	0.1521	0.3388*	0.0318	0.1764
	(0.1497)	(0.1782)	(0.1095)	(0.1246)
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Sample	Matched	Matched	Full	Full
Observations	404	349	775	669

Note: The dependent variable is value-added of teachers who change district and type of district in a given year. The variable *IS* equals 1 for 101 districts classified as individual-salary. The variable *post* equals 1 for years following 2011. In the full sample, the control group are 112 districts classified as salary-schedule. In the matched sample, the control group are 64 salary-schedule districts. Standard errors in parentheses are clustered at the district level.

Table 6: OLS - Dependent variable is average value-added

	IS	SS		All districts	
	(1)	(2)	(3)	(4)	(5)
mover	-0.0550**	0.0236	-0.0185	0.0230	-0.0184
	(0.0272)	(0.0523)	(0.0388)	(0.0518)	(0.0385)
mover * post	0.0510	-0.0599	0.0100	-0.0611	0.0091
	(0.0523)	(0.0778)	(0.0630)	(0.0769)	(0.0624)
IS * post				0.0031	0.0025
				(0.0105)	(0.0090)
IS * mover				-0.0775	-0.0363
				(0.0583)	(0.0469)
IS * mover * post				0.1126	0.0431
				(0.0928)	(0.0811)
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Sample	Full	Matched	Full	Matched	Full
Observations	43641	26692	56825	70333	100466

Note: The dependent variable is value-added of teachers in individual-salary districts (column 1), in salary-schedule districts (columns 2-3), and in all districts (columns 4-5). The variable *mover* equals 1 for teachers changing district in a given year. The variable *post* equals 1 for years following 2011. The variable *IS* equals 1 for 101 districts classified as individual-salary. In the full sample, the control group are 112 districts classified as salary-schedule. In the matched sample, the control group are 64 salary-schedule districts. Standard errors in parentheses are clustered at the district level.

Table 7: OLS - Dependent variable is ln(salary)

	IS	SS		All districts	
	(1)	(2)	(3)	(4)	(5)
mover	-0.021**	-0.013**	-0.009**	-0.013**	-0.011**
	(0.0049)	(0.0026)	(0.0025)	(0.0030)	(0.0025)
mover * post	0.020**	0.008*	0.008*	0.005	0.006
	(0.0051)	(0.0049)	(0.0044)	(0.0052)	(0.0051)
mover * IS				-0.008	-0.007
				(0.0054)	(0.0049)
IS * post				-0.002	-0.006
				(0.0067)	(0.0058)
mover * IS * post				0.015**	0.011
				(0.0073)	(0.0069)
Observations	152817	97391	196970	250208	349787
Individual FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Sample	Full	Matched	Full	Matched	Full

Note: The dependent variable is the natural logaritm of salaries. The variable *mover* equals 1 for teachers changing district in a given year. The variable *post* equals 1 for years after 2011. Controls include a full set of interactions between two-years seniority dummies and dummies for having a Bachelor, Master, or Ph.D. In the full sample, the control group are 112 districts classified as salary-schedule. In the matched sample, the control group are 64 salary-schedule districts. Standard errors in parentheses are clustered at the district level.

Table 8: OLS - Dependent variable is value-added of exiters

	(1)	(2)	(3)	(4)
IS	0.0416	0.0558	0.0283	0.0379
	(0.0453)	(0.0479)	(0.0380)	(0.0422)
IS * post	-0.1440**	-0.1654**	-0.1153**	-0.1311**
	(0.0549)	(0.0579)	(0.0561)	(0.0570)
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Sample	Matched	Matched	Full	Full
Observations	2344	2270	3530	3399

Note: The dependent variable measures value-added of teachers who exit in a given year. The variable *IS* equals 1 for 101 districts classified as individual-salary. The variable *post* equals 1 for years following 2011. In the full sample, the control group are 112 districts classified as salary-schedule. In the matched sample, the control group are 64 salary-schedule districts. Standard errors in parentheses are clustered at the district level.

Table 9: OLS - Dependent variable is average value-added

	IS	SS		All districts	
	(1)	(2)	(3)	(4)	(5)
exit	0.0425	-0.0108	0.0009	-0.0112	0.0006
	(0.0263)	(0.0363)	(0.0305)	(0.0361)	(0.0306)
exiter * post	-0.0647*	0.0896*	0.0583	0.0888*	0.0584
	(0.0350)	(0.0476)	(0.0465)	(0.0472)	(0.0467)
IS * post				0.0055	0.0059
				(0.0094)	(0.0078)
IS * exiter				0.0536	0.0420
				(0.0446)	(0.0403)
IS * exiter * post				-0.1532**	-0.1231**
				(0.0587)	(0.0583)
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Sample	Full	Matched	Full	Matched	Full
Observations	40646	24780	53121	65426	93767

Note: The dependent variable measures value-added of teachers in individual-salary districts (column 1), in salary-schedule districts (columns 2-3), and in all districts (columns 4-5). The variable *exit* equals 1 for teachers exiting public schools at the end of a given year. The variable *post* equals 1 for years following 2011. The variable *IS* equals 1 for 101 districts classified as individual-salary. In the full sample, the control group are 112 districts classified as salary-schedule. In the matched sample, the control group are 64 salary-schedule districts. Standard errors in parentheses are clustered at the district level.

Table 10: OLS - Dependent variable is ln(salary)

	IS	SS		All districts	
	(1)	(2)	(3)	(4)	(5)
exit	-0.011**	-0.013**	-0.009**	-0.018**	-0.013**
	(0.0026)	(0.0036)	(0.0030)	(0.0038)	(0.0029)
exit * post	-0.011**	0.003	-0.001	0.007*	0.002
	(0.0054)	(0.0031)	(0.0021)	(0.0038)	(0.0025)
exit * IS				0.009*	0.005
				(0.0052)	(0.0041)
IS * post				0.003	0.000
				(0.0061)	(0.0047)
exit * IS * post				-0.021**	-0.016**
				(0.0059)	(0.0054)
Observations	140473	89403	182343	229876	322816
Individual FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Sample	Full	Matched	Full	Matched	Full

Note: The dependent variable is the natural logaritm of salaries. The variable *exit* equals 1 for teachers exiting public schools at the end of a given year. The variable *post* equals 1 for years after 2011. Controls include a full set of interactions between two-years seniority dummies and dummies for having a Bachelor, Master, or Ph.D. In the full sample, the control group are 112 districts classified as salary-schedule. In the matched sample, the control group are 64 salary-schedule districts. Standard errors in parentheses are clustered at the district level.

Table 11: OLS - Dependent variable is value-added

	(1)	(2)	(3)	(4)
IS * post	0.0068	0.0038	0.0102	0.0062
	(0.0075)	(0.0087)	(0.0091)	(0.0101)
Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Sample	Full	Full	Matched	Matched
Observations	107975	103160	74873	72134

Note: The dependent variable measures teacher value-added. The variable *IS* equals 1 for 101 districts classified as individual-salary. The variable *post* equals 1 for years following 2011. In the full sample, the control group are 112 districts classified as salary-schedule. In the matched sample, the control group are 64 salary-schedule districts. All regressions include district fixed effects. Standard errors in parentheses are clustered at the district level.

Table 12: OLS - Dependent variable is average test scores

	Math	Reading	ELA	All	Math	Reading	ELA	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS * post	0.063*	0.032	0.019	0.043	0.054	0.055	0.106**	0.053*
	(0.0320)	(0.0311)	(0.0416)	(0.0268)	(0.0343)	(0.0366)	(0.0538)	(0.0298)
School, Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
VA controls	None	None	None	None	Mean	Mean	Mean	Mean
Observations	20557	20557	7788	48902	18668	16018	4772	39458

Note: The dependent variable is average test scores at the grade-school-subject-year level for mathematics, reading, and language arts, for grades 3-8 and 10, standardized within each grade-subject level using the 2007 state distribution of test scores. The variable *IS* equals 1 for 101 districts classified as individual-salary. The variable *post* equals 1 for years following 2011. The control includes 64 salary-schedule districts. The sample is obtained using a Mahalanobis matching procedure based on district observables. Standard errors in parentheses are clustered at the school level.

Table 13: Estimates of parameters of the model

	Teacher				District	
parameter	interpretation	estimate (1)	elasticity (2)	parameter	interpretation	estimate (3)
α_z	salary ($1,000)	0.0062*	0.3248	β	value-added	52.1745***
		(0.0037)				(0.0013)
	distance	-0.0317***	-0.5227		seniority	1.3039***
		(0.0036)				(0.0049)
	incumbent	8.496***	0.9698		Master	10.9725***
		(0.0038)				(0.0023)
	% poor students	0.0009	0.0323	σ_ε	st. dev. of shock	1.3219***
		(0.0052)				(0.0054)
	urban	0.3043***	0.2545			
		(0.0034)				
α_0	outside option	6.2256***				
		(0.0059)				

Note: Estimates of the parameters of the structural model. Parameters are estimated by maximum likelihood. Defining p_{ij} as the probability that teacher i moves to district j, the elasticity of p_{ij} to a continuous job characteristic z_{ij} implied by the logit assumption on the error term of teachers' utility is $\beta_z(1 - p_{ij})z_{ij}$. The elasticity of urban and incumbent is defined as $(1 - p_{ij})(1 - \exp(-\beta_z))$. Elasticities are evaluated at the median of each variable, equal to $54,000 for salary, 17 miles for distance, and 37 percent for the share of poor students. Standard errors are computed numerically.

Table 14: Model fit

		2012 (estimation year)		2009 (testing year)	
moment		model (1)	data (2)	model (3)	data (4)
p(move)		0.0001	0.0062	0.00009	0.0044
	VA>0	0.0001	0.0046	0.0001	0.0052
	VA<0	0.0001	0.0071	0.0001	0.0042
p(exit)		0.0623	0.0620	0.0634	0.0314
	VA>0	0.0637	0.0750	0.0652	0.0340
	VA<0	0.0641	0.0645	0.0649	0.0302

Note: Target rates are obtained from the data, for the years 2009 and 2012. Simulation rates are obtained from the model and using the parameter estimates in Table 13.

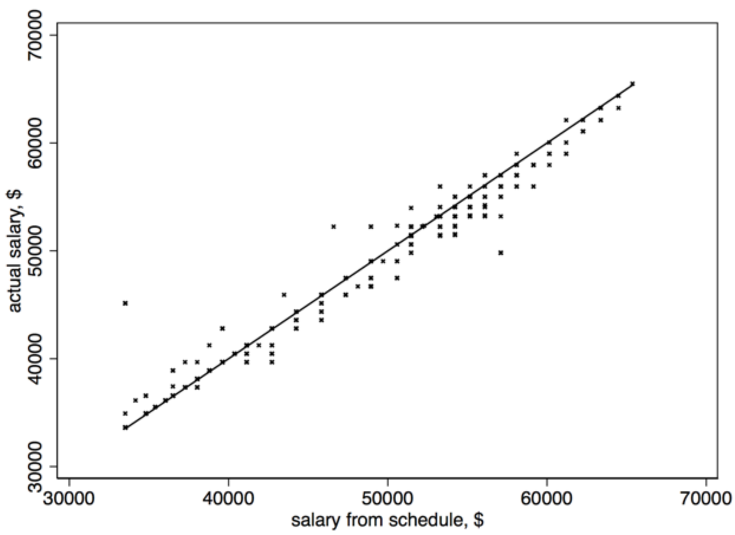
Appendix A - Additional Tables and Figures

Figure A1: Salary schedule - Racine School District, 2016

Step	BA	BA+12	BA+24	MA
1	40,593	42,784	44,976	47,169
2	41,526	43,717	45,909	48,516
3	42,459	44,651	46,842	49,864
4	43,392	45,584	47,775	51,211
5	44,325	46,517	48,709	52,560

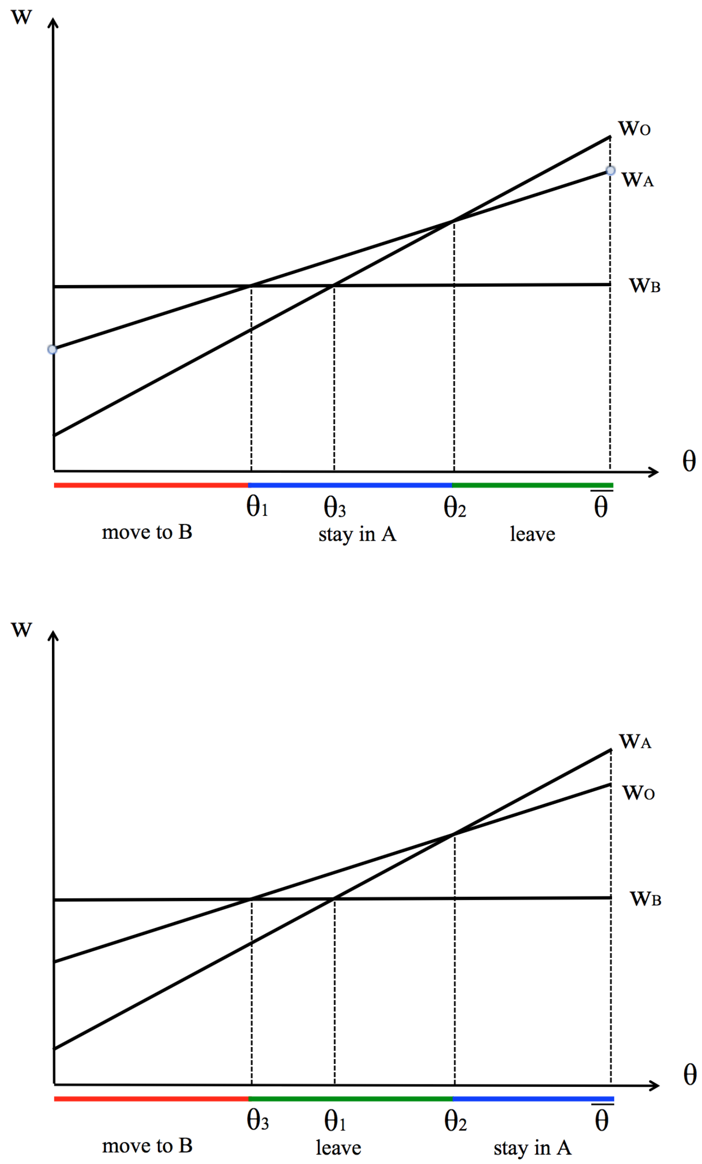
Notes: Example of a section of the salary schedule used to determine teacher salaries in Racine School District. Source: http://www.rusd.org.

Figure A2: Actual salary and schedule salary - Madison Metropolitan School District, 2011



Notes: The y-axis shows total annual salary as reported in the data, the vertical axis shows salary as calculated using the district salary schedule. The red line is the 45-degrees line. The sample is restricted to all teachers without a Master degree employed in the Madison Metropolitan School District in 2011. The salary schedule is taken from http://www.madisonteachers.org

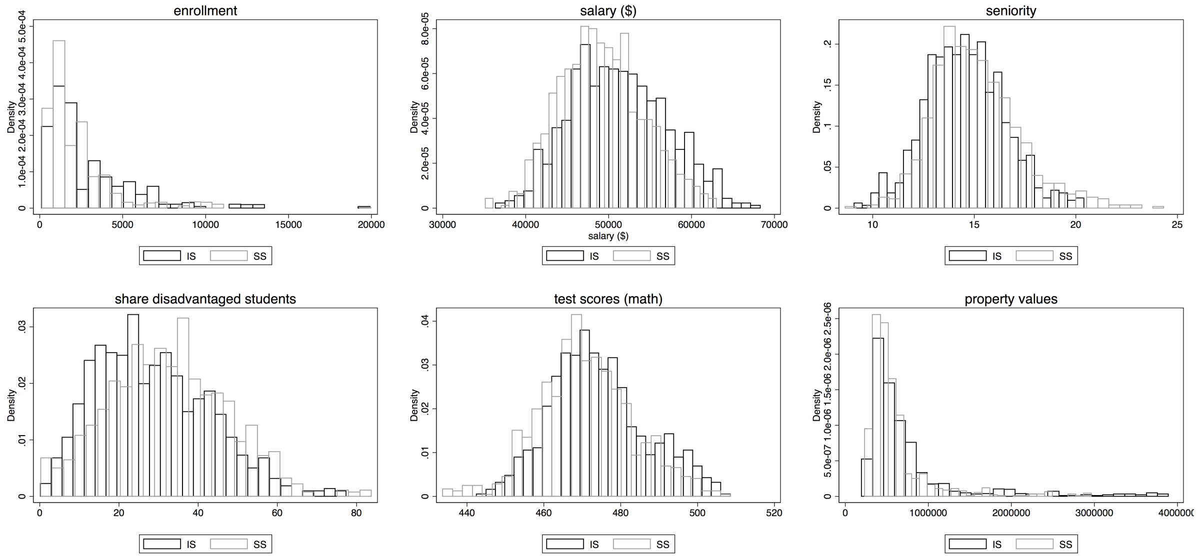
Figure A3: Conceptual framework: movers and leavers, case 1 (top panel) and case 2 (bottom panel)



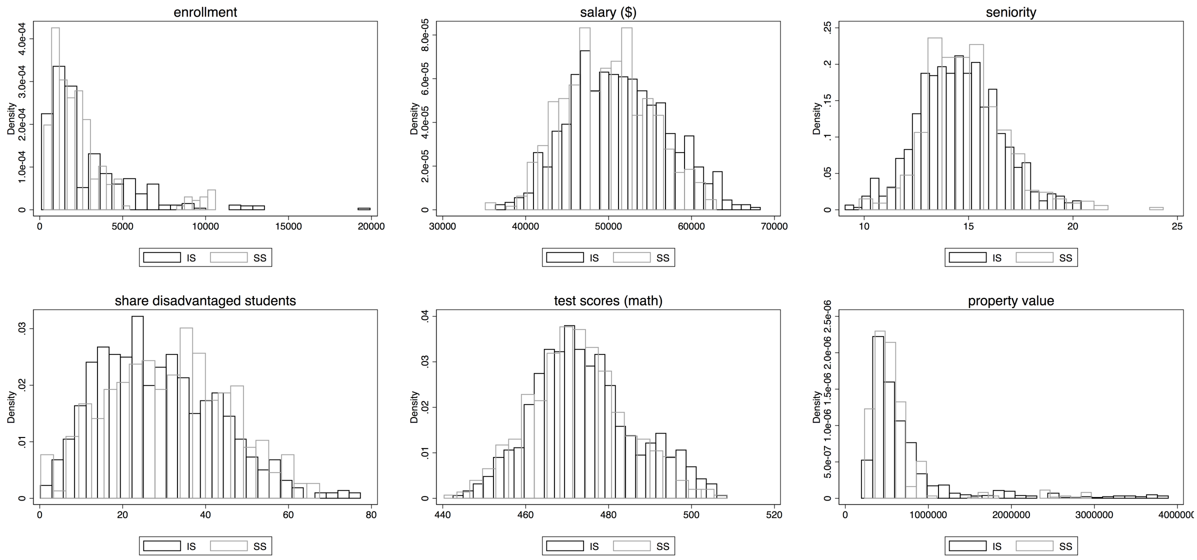
Notes: Values of θ and move/exit decisions for incumbents in district A, as described in the conceptual framework in Section 5.

Figure A4: Distribution of average district-level characteristics

Full sample

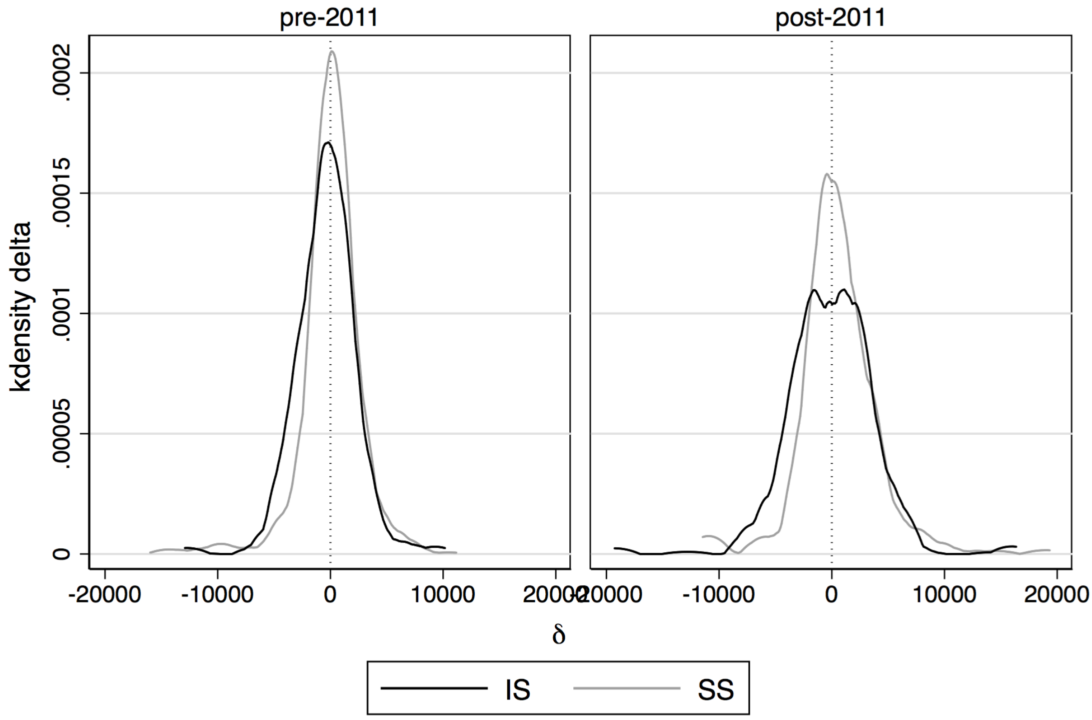


Matched sample



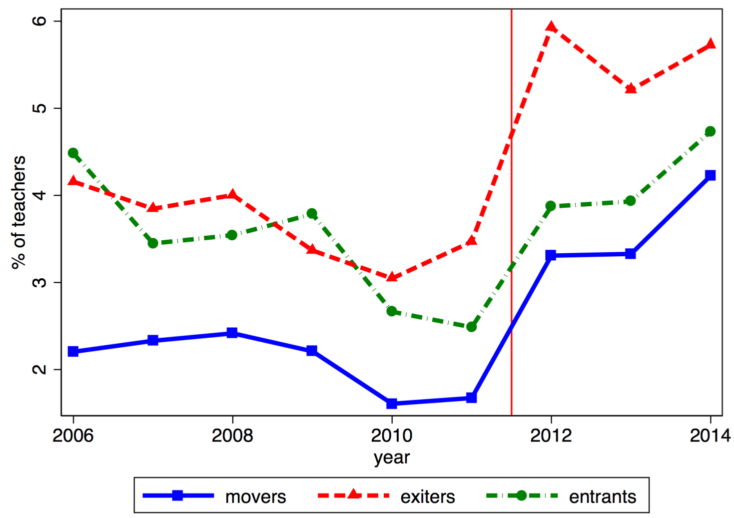
Notes: Distribution of district-level characteristics of individual-salary and salary-schedule districts in the period 2007-2011. The individual-salary subsample includes 101 districts. In the full sample, the salary-schedule subsample includes 122 districts. In the matched sample, the salary-schedule subsample includes 64 districts. The full subsample covers 83 percent of the total student population. The matched subsample covers 59 percent of the total student population.

Figure A5: Distribution of the post-Act 10 correlation between salary residuals and teacher value-added



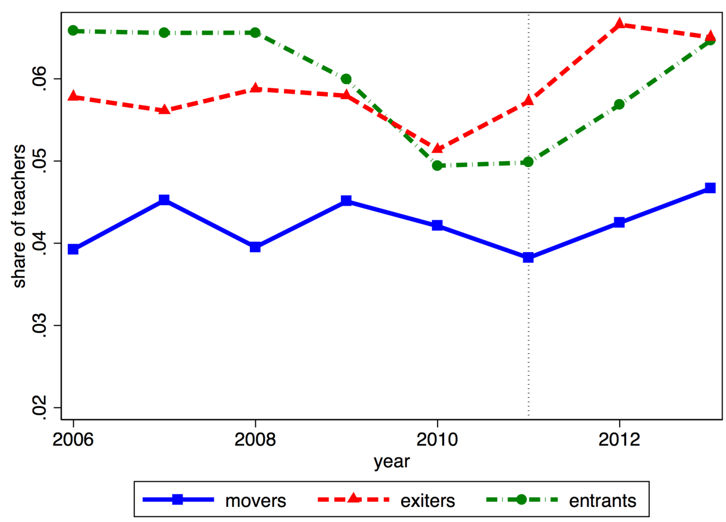
Notes: Distribution of the coefficient δ, , OLS estimate from the regression $w_{ijt} = \delta_j f(q_i) + \gamma X_{it} + \tau_t + \varepsilon_{ijt}$. The variable w_{ijt} is salary of teacher i working in district j in year t, the variable q_i is value-added, the vector X_{it} includes two-years seniority dummies interacted with education dummies, and τ_t are year fixed effects. The function $f(x)$ is a standard logistic: $f(x) = 1/(1+e^{-x})$. The model is estimated separately for each district and for the periods before and after Act 10. The sample is restricted to 110 individual-salary and 122 salary-schedule districts with information on post-2011 teacher contracts, enrolling 83 of the total student population.

Figure A6: Share of teachers entering teaching, moving across districts, and leaving, 2008-2014



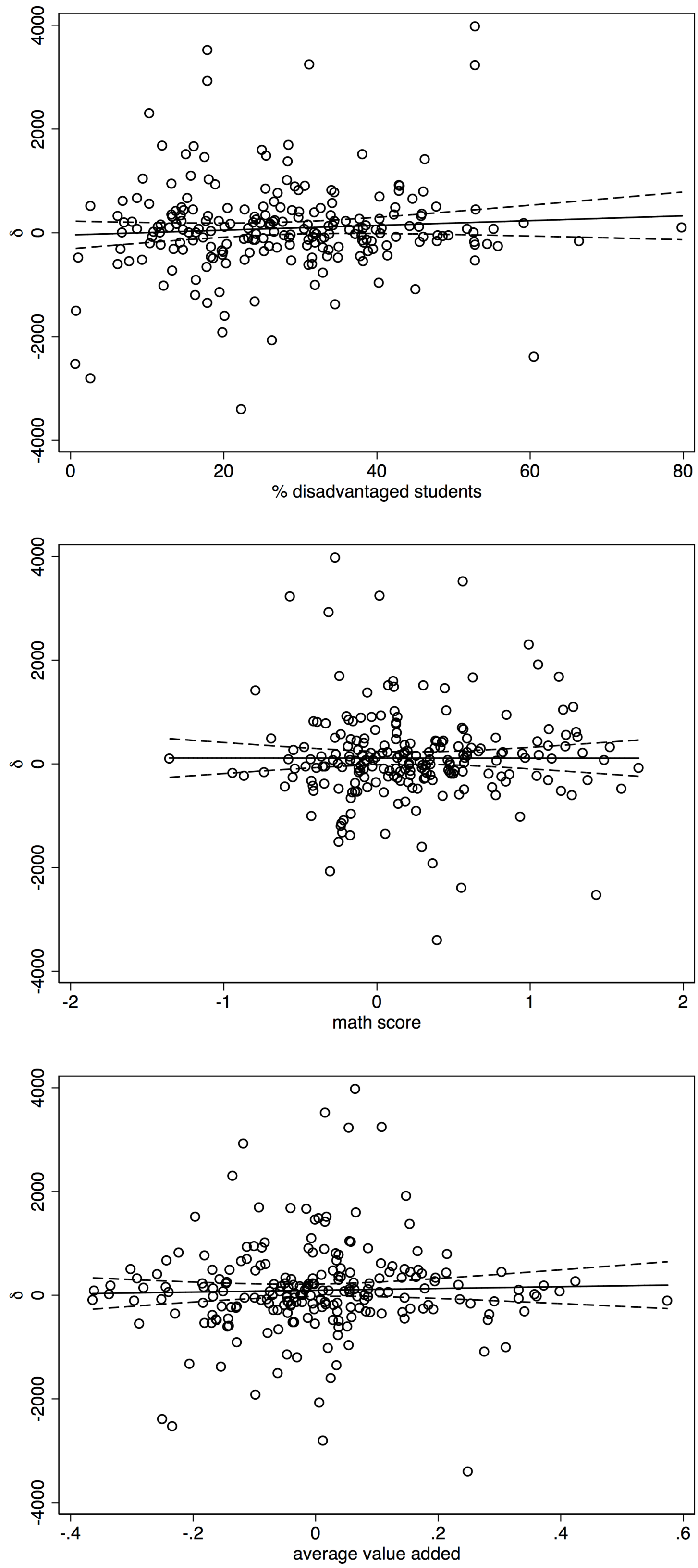
Notes: Share of Wisconsin teachers entering public schools, moving across districts, and exiting public schools over time over time. Each share is defined as the total number of teachers entering, moving, or leaving, divided by the total number of teachers employed in Wisconsin public schools in each year.

Figure A7: Share of teachers entering teaching, moving across districts, and leaving, Minnesota 2006-2013



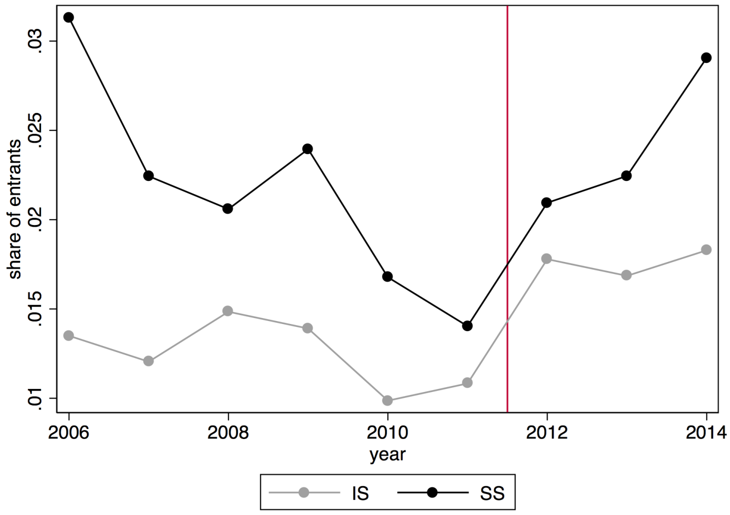
Notes: Share of Minnesota teachers entering public schools, moving across districts, and exiting public schools over time over time. Each share is defined as the total number of teachers entering, moving, or exiting, divided by the total number of teachers employed in Minnesota public schools in each year.

Figure A8: Districts' pre-Act 10 characteristics and δ - Correlation



Notes: Scatter plots of district characteristics (vertical axis) against the coefficient δ_j, OLS estimate from the regression $w_{ijt} = \delta_j f(q_i) + \gamma X_{it} + \tau_t + \varepsilon_{ijt}$. District characteristics are calculated as district value-averages for the years 2007-2011. The sample is restricted to 223 districts with non-missing contract data, enrolling 83 percent of the population of students.

Figure A9: Share of teachers entering public schools

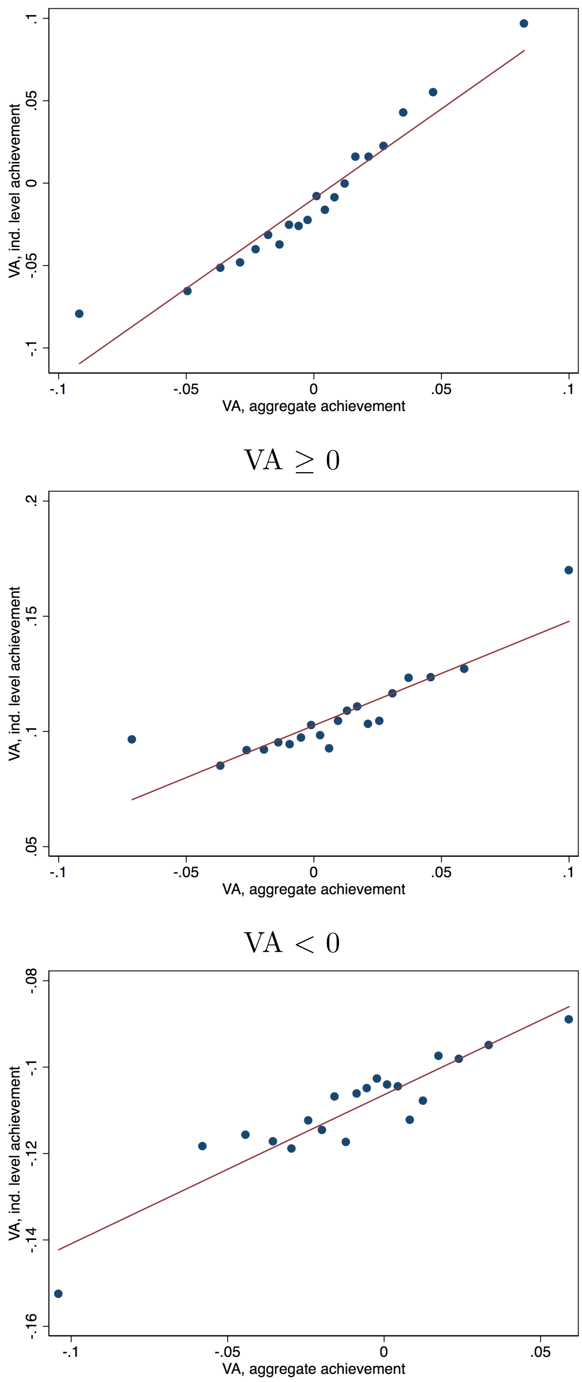


Notes: Share of new teachers in the two types of districts over time. Each share is defined as the total number of new teachers, divided by the total number of teachers employed in Wisconsin public schools in each year in districts with non-missing contracts information. The individual-salary subsample includes 110 districts, the salary-schedule subsample includes 122 districts.

Figure A10: Counts of teachers with and without value-added

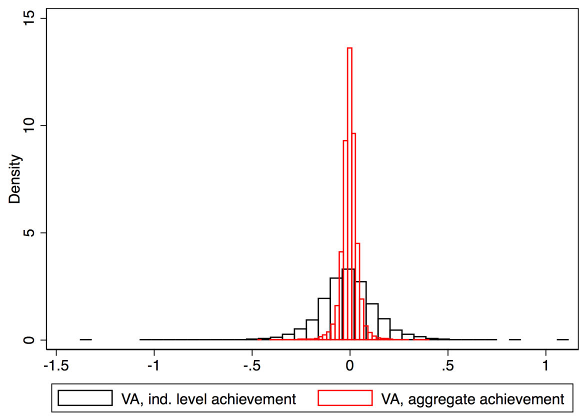
Notes: Counts of teachers in mathematics and readings, with and without an estimate of value-added. The individual-salary subsample includes 101 districts, the salary-schedule subsample includes 122 districts. The subsample covers 83 percent of the total student population.

Figure A11: Binned scatterplot, VA computed with individual-level data vs. VA computed with aggregate data (NYC sample)



Notes: Binned scatterplot of value-added estimated with individual-level student data (vertical axis) and value-added estimated using aggregate data (horizontal axis), for mathematics teachers in the New York City school district between 2006 and 2010. Value-added measures are estimated using the models in Appendix D.

Figure A12: Histogram, VA computed with individual-level data vs. VA computed with aggregate data (NYC sample)



Notes: Histogram of value-added estimated with individual-level student data (black) and value-added estimated using aggregate data (red), for mathematics teachers in the New York City school district between 2006 and 2010. Value-added measures are estimated using the models in Appendix D.

Table A1: District characteristics, by availability of Employee Handbook

	Unavailable	Available	Difference
enrollment	680.2	2996.6	-2316.4***
	(592.3)	(5418.2)	(222.2)
% black students	1.271	3.042	-1.531***
	(1.584)	(6.155)	(0.305)
% disadvantaged students	40.66	34.91	6.032***
	(15.22)	(14.82)	(0.854)
salary ($)	48219.4	51346.1	-3134.1***
	(4671.6)	(5201.3)	(279.1)
salary, experience$\leq$5 ($)	36838.5	38383.6	-1553.5***
	(3612.0)	(3612.2)	(203.2)
salary, experience>20 ($)	56039.7	60892.9	-4835.1***
	(5865.3)	(6804.8)	(359.1)
experience	14.75	14.16	0.585***
	(2.716)	(1.945)	(0.132)
Bachelor	0.580	0.470	0.110***
	(0.167)	(0.141)	(0.00864)
Master	0.418	0.525	-0.107***
	(0.167)	(0.141)	(0.00865)
Ph.D.	0.000593	0.00116	-0.000571***
	(0.00366)	(0.00356)	(0.000203)
VA	-0.00149	0.00515	-0.00667
	(0.247)	(0.190)	(0.0123)
math test scores	471.7	473.9	-2.266***
	(12.00)	(12.60)	(0.703)
reading test scores	476.8	477.1	-0.274
	(9.712)	(9.573)	(0.550)
property value per-pupil	997153.1	713766.2	283387.0***
	(1373067.7)	(741929.9)	(61193.2)
N	204	223	

Note: Means and standard deviations (in parentheses) for 101 individual-salary districts and 122 salary-schedule districts with non-missing handbook information, and 203 districts with missing handbook information.

Table A2: OLS - Dependent variable is log(salary)

	IS (1)	SS (2)	All (3)
math	0.005	0.005**	0.004**
	(0.0032)	(0.0019)	(0.0019)
math * post	-0.007**	-0.002	-0.002
	(0.0030)	(0.0025)	(0.0023)
technology	0.009**	0.012**	0.011**
	(0.0042)	(0.0035)	(0.0035)
technology * post	0.001	0.001	0.001
	(0.0058)	(0.0049)	(0.0049)
special ed	-0.025	0.001	-0.002
	(0.0165)	(0.0053)	(0.0051)
special ed * post	-0.011	0.007*	0.006*
	(0.0157)	(0.0037)	(0.0036)
ES	0.007	-0.002	-0.003
	(0.0062)	(0.0048)	(0.0050)
ESL * post	-0.001	0.006	0.005
	(0.0064)	(0.0056)	(0.0056)
IS * post			-0.004
			(0.0062)
math * IS			0.001
			(0.0040)
math * IS * post			-0.006
			(0.0037)
technology * IS			-0.001
			(0.0056)
technology * IS * post			0.000
			(0.0077)
special ed * IS			-0.016
			(0.0114)
special ed * IS * post			-0.019
			(0.0172)
ESL * IS			0.013
			(0.0084)
ESL * IS * post			-0.008
			(0.0086)
Observations	159909	207227	367136
Year FE	Yes	Yes	Yes
Grade FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Note: The dependent variable is the natural logaritm of salaries. The variable *math* equals one for math teachers, *technology* equals one for technology teachers, *special ed* equals one for special education teachers, and *ESL* equals one for English-as-second-language teachers. Controls include a full set of two-years seniority dummies interacted with education dummies (Bachelor, Master, and Ph.D.). The IS sample (column 1) includes 101 individual-salary districts, the SS sample (column 2) includes 122 salary-schedulee districts. Standard errors in parentheses are clustered at the district level.

Table A3: Probit - Propensity score matching, dependent variable is =1 for individual-salary districts

	(1)
enrollment	-1.99e-05
	(2.95e-05)
urban	-0.238
	(0.475)
suburban	0.0595
	(0.260)
% disadvantaged students	-0.00525
	(0.00814)
salary ($)	0.000121
	(8.00e-05)
salary ($)	7.69e-05
	(6.37e-05)
salary ($)	-8.07e-05
	(5.26e-05)
experience	-0.177**
	(0.0753)
Bachelor	-2.163
	(5.956)
Master	-2.463
	(5.947)
property value	2.37e-07
	(1.66e-07)
Constant	0.867
	(6.288)
Observations	222

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Estimates of a probit model used to compute the propensity score to match individual-salary districts to salary-schedule districts. The dependent variable equals 1 for individual-salary districts. The regressors are averages of district-level variables for the years 2006-2011.

Table A4: OLS - Dependent variable is value-added, Alternative matched sample n.1

	Movers		Exiters		All	
	(1)	(2)	(3)	(4)	(5)	(6)
IS	0.1505	0.1850	0.0145	0.0119		
	(0.0966)	(0.1139)	(0.0586)	(0.0628)		
IS * post	-0.0957	-0.0969	-0.0805	-0.0964	0.0118	0.0119
	(0.1788)	(0.1908)	(0.0832)	(0.0906)	(0.0106)	(0.0110)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	346	296	2247	2180	71528	69022

Note: The dependent variable measures value-added of teachers who change district in a given year from individual-salary districts (column 1) and from salary-schedule districts (column 2), teachers who exit (column 3), and all teachers (column 4). The variable *IS* equals 1 for 101 districts classified as individual-salary. The variable *post* equals 1 for years following 2011. The control group are 61 salary-schedule districts. The sample is obtained using a Mahalanobis matching procedure based on enrollment, location (urban, suburban, or rural), property values, and the share of disadvantaged students. Standard errors in parentheses are clustered at the district level.

Table A5: OLS - Dependent variable is value-added, Alternative matched sample n.2

	Movers		Exiters		All	
	(1)	(2)	(3)	(4)	(5)	(6)
IS	-0.0499	-0.0570	0.0141	0.0216		
	(0.1097)	(0.1155)	(0.0525)	(0.0547)		
IS * post	0.1594	0.2860	-0.1071*	-0.1270*	0.0056	-0.0023
	(0.1817)	(0.1920)	(0.0646)	(0.0650)	(0.0104)	(0.0115)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	325	283	2159	2097	69371	67045

Note: The dependent variable measures value-added of teachers who change district in a given year from individual-salary districts to salary-schedule districts or in the opposite direction (columns 1-2), teachers who exit (columns 3-4), and all teachers (columns 5-6). The variable *IS* equals 1 for 101 districts classified as individual-salary. The variable *post* equals 1 for years following 2011. The control group are 61 salary-schedule districts. The sample is obtained using nearest-neighbor propensity score matching based on enrollment, location (urban, suburban, or rural), property values, the share of disadvantaged students, average salaries for all teachers, for teachers with less than 5 years of seniority, and for teachers with more than 20 years of seniority, average seniority, and the share of teachers with a BA or Master degree. Standard errors in parentheses are clustered at the district level.

Table A6: OLS - Dependent variable is average test scores (Full sample)

	Math	Reading	ELA	All	Math	Reading	ELA	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IS * post	0.114**	0.073**	0.069*	0.089**	0.105**	0.091**	0.122**	0.106**
	(0.0281)	(0.0271)	(0.0372)	(0.0241)	(0.0302)	(0.0303)	(0.0475)	(0.0259)
School, Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
VA controls	None	None	None	None	Mean	Mean	Mean	Mean
Observations	31114	31114	11830	74058	27525	23898	7238	58661

Note: The dependent variable is average test scores at the grade-school-subject-year level for mathematics, reading, and language arts, for grades 3-8 and 10, standardized within each grade-subject level using the 2007 state distribution of test scores. The variable *IS* equals 1 for 101 districts classified as individual-salary. The variable *post* equals 1 for years following 2011. The control includes 122 districts classified as salary-schedule. Standard errors in parentheses are clustered at the district level.

Table A7: Value-added: variance of effects

	Variance	
group	teacher effect (w/shrinkage)	teacher effect (w/out shrinkage)
Overall, elementary	0.190	0.240
Mathematics, elementary	0.218	0.253
Reading, elementary	0.095	0.228
Overall, high school	0.170	0.200
Mathematics, high school	0.183	0.201
Reading, high school	0.144	0.199

Note: Variance of teacher effects estimated using the method described in Appendix D.

Appendix B - Adjusting Teacher Seniority in The Data

Data in the PI-1202 Fall Staff Report - All Staff Files include a variable recording total seniority, expressed in months. I divide this variable by 10 to obtain a measure of the number of years of seniority. In principle, information contained in this variable should be sufficient to place each teacher on the salary schedule of the district where she is employed, before Act 10. At the same time, teachers who appear identical on the basis of seniority and academic qualifications should earn the same salary when employed in the same district.

The sample, however, contains a non-trivial number of cases where this is not true. This might happen for at least two reasons. The first is the inability to fully observe each teacher's assignment of extra duties (i.e. non-instructional tasks such as recess monitoring, coaching, etc.), which are associated with additional pay. The presence of this unobserved extra pay introduces a source of measurement error in salaries. The second is the imperfect match between total years of seniority, as reported in the data, with the actual level of seniority used to place a teacher on the salary schedule. This might happen if districts discount teaching experience outside the district, and/or if advancements along the schedule are made contingent to the acquisition of specific credentials.

In order to partially reconcile the mismatch between these two measures of seniority - the one reported in the data and the one used to place teachers on the schedule, I adjust years of experience using the following procedure.

1. I use the empirical pre-reform distribution of salaries in each district and year to back out the relevant salary schedule. I do this by dividing teachers in cells defined by district, year, academic qualification (Bachelor, Master, and Ph.D.), and two-years experience intervals, and I calculate the modal salary for each cell.

2. I use the constructed schedule to assess the extent to which a teacher's seniority is off the schedule, given her recorded level of seniority and academic qualifications. To do so, I match each teacher's observed salary with the level of salary on the schedule at each experience level, and for the successful matches I compare the level of seniority on the schedule with that recorded in the data.

3. For the teachers whose salary is off the schedule, I substitute the level of seniority with the one specified by the salary schedule.

Figure A2 plots actual salary and salary as determined from the schedule for 633 full-time teachers with a Bachelor employed in the Madison Metropolitan School District in 2011, after having adjusted seniority as described above. Two-hundred and fifty-six teachers on the 45 degree red line (40 percent) are paid as determined by the salary schedule. Three-hundred and sixty-one teachers below the red line (57 percent) are paid 2.3 percent less on average than what would result from the schedule based on their total years of experience as reported in the data. Sixteen teachers above the red line (3 percent) are instead paid 4.6 percent more on average than the schedule. This figure shows that the most frequent cause of the observed difference between observed salary and salary schedule is due to mismatch between the reported seniority and the level of seniority used to place teachers on the schedule (which might result in a lower salary), rather than to extra duties (which lead to a higher salary). This difference is, however, rather small.

Appendix C - Proofs of Propositions

Proof of Proposition 1 The share of teachers moving at $t = 0$ is zero. Utility maximization implies that a teacher with quality θ will move from district A to district B if and only if $w_A < w_B$.[42] As a result, the share of teachers who move from A to B is:

$$s_{AB} = Pr(\alpha\bar{w} + \beta\theta < \bar{w}) = \Phi(\frac{(1-\alpha)\bar{w} - \beta\mu}{\beta\sigma}) \tag{18}$$

where $\Phi(.)$ denotes the CDF of a standard normal. Analogously, the share of teachers who move from B to A is:

$$s_{BA} = Pr(\text{move from B to A}) = P(\alpha\bar{w} + \beta\theta > \bar{w}) = 1 - \Phi(\frac{(1-\alpha)\bar{w} - \beta\mu}{\beta\sigma}) \tag{19}$$

As long as $\beta > 0$, $s_{AB} > 0$ and $s_{BA} > 0$. □

Proof of Proposition 2 Define $k = (1-\alpha)w/\beta > 0$ and $\kappa = (k-\mu)/\sigma$. By the properties of a truncated normal, the average quality of teachers moving from A to B is

$$\widetilde{\theta}_{AB} = \mathbb{E}_\theta(\theta|\alpha\bar{w} + \beta\theta < \bar{w}) = \mu - \sigma\frac{\phi(\kappa)}{\Phi(\kappa)} \tag{20}$$

where $\phi(.)$ is the PDF of a standard normal. Similarly, the average quality of teachers moving from B to A is

$$\widetilde{\theta}_{BA} = \mathbb{E}_\theta(\theta|\alpha\bar{w} + \beta\theta > \bar{w}) = \mu + \sigma\frac{\phi(\kappa)}{1-\Phi(\kappa)} \tag{21}$$

It is easy to see that $\widetilde{\theta}_{AB} < \mu$ and $\widetilde{\theta}_{BA} > \mu$. The result follows. □

Proof of Proposition 3 The share of teachers exiting at $t = 0$ is zero. Utility maximization implies that a teacher with quality θ working in A will exit if and only if $w_O > \max\{w_A, w_B - m\}$. Similarly, a teacher with quality θ working in B will exit if and only if $w_O > \max\{w_A - m, w_B\}$. Since all teachers working in districts A and B have quality $\theta < \bar{\theta}$, the share of teachers exiting from B in $t = 1$, s_{BO}, is equal to 0.

To calculate the share of teachers exiting from A, s_{AO}, I define some useful quantities. I define θ_1 as the quality of a teacher currently working in A who is indifferent between exiting and moving to B: $\theta_1 = [(1-\gamma)\bar{w} - m]/\lambda$. Similarly, I define θ_2 as the quality of a teacher currently working in A who is indifferent between exiting and remaining in A: $\theta_2 = [(\gamma - \alpha)\bar{w}]/(\beta - \lambda)$.[43] Lastly, I define θ_3 as the quality of a teacher working in A who is indifferent between staying in A and moving to B: $\theta_3 = [(1-\alpha)\bar{w} - m]/\beta$. I assume $\theta_2 < \bar{\theta}$ and $\theta_2 > \max\{\theta_1, \theta_3\}$, i.e. there always exist both teachers who prefer to exit A, and teachers who prefer to stay, to rule out non-interesting cases. Under these assumptions, the following cases can occur:

- $\theta_1 < \theta_3$. In this case, described in the top panel of Figure A3, three groups of teachers exists among the incumbents in A: those with $\theta < \theta_1$ (red section), who will be better off moving to B; those with $\theta : \theta_1 < \theta < \theta_2$ (green section), who will be better off exiting; and those with $\theta > \theta_2$, who will be better off staying (blue section).

[42] I assume, without loss of generality, that moving costs are zero for all teachers.
[43] I assume θ_2 exists and is finite.

- $\theta_3 < \theta_1$. In this case, described in the bottom panel of Figure A3, teachers with $\theta < \theta_3$ (red section) will be better off moving to B; those with $\theta : \theta_3 < \theta < \theta_2$ (blue section) will be better off staying in A; and those with $\theta > \theta_2$ (green section) will be better off exiting.

  As a result, s_{AO} can be written as:

$$s_{AO} = \begin{cases} Pr(\theta_1 < \theta < \theta_2) = \Phi(\frac{\theta_2 - \mu}{\sigma}) - \Phi((\frac{\theta_1 - \mu}{\sigma}) & \text{if } \theta_1 < \theta_3 \\ Pr(\theta > \theta_2) = 1 - \Phi((\frac{\theta_2 - \mu}{\sigma}) & \text{if } \theta_3 < \theta_1 \end{cases} \tag{22}$$

  which is positive under the above assumptions.

□

Proof of Proposition 4 Define $\rho = (\bar{\theta} - \mu)/\sigma$, $\upsilon = (\theta_1 - \mu)/\sigma$, and $\varphi = (\theta_2 - \mu)/\sigma$. Note first that the average quality of teachers in A and B before the change in the salary scheme is $\mathbb{E}_\theta(\theta|\theta < \bar{\theta}) = \mu - \sigma\phi(\rho)/\Phi(\rho) < \mu$. By the properties of a truncated normal, the average quality of teachers exiting from A is

$$\widetilde{\theta}_{AO} = \begin{cases} \mathbb{E}_\theta(\theta|\theta_1 < \theta < \theta_2) = \mu - \sigma\frac{\phi(\varphi) - \phi(\upsilon)}{\Phi(\varphi) - \Phi(\upsilon)} & \text{if } \theta_1 < \theta_3 \\ \mathbb{E}_\theta(\theta|\theta > \theta_2) = \mu + \sigma\frac{\phi(\varphi)}{1 - \Phi(\varphi)} & \text{if } \theta_3 < \theta_1 \end{cases} \tag{23}$$

If $\phi(\rho)/\Phi(\rho) < (\phi(\varphi) - \phi(\upsilon))/(\Phi(\varphi) - \Phi(\upsilon))$, the first case implies the result. □

Appendix D - Estimating Teacher Value Added Using Aggregate Achievement Data

Teacher value-added is a measure of teacher quality first proposed by Hanushek (1971) and Murnane (1975), and developed more recently by Rockoff (2004), Rivkin et al. (2005), Aaronson et al. (2007), Kane and Staiger (2008), and Chetty et al. (2014a). The idea behind this measure is to rate teachers based on their past students' test scores. Chetty et al. (2014a) define value-added as "the individual teacher's contribution to achievement growth", or in other words the component of test scores attributable to each teacher once other student characteristics have been controlled for.

The starting point for the estimation of teacher value-added is the following model of achievement (Kane and Staiger, 2008; Chetty et al., 2014a):

$$A_{kit} = \beta X_{kt} + \omega_{kit}$$

where A_{kit} is achievement of student k, taught by teacher i in classroom c at time t, and X_{kt} is a vector of time-varying student control variables. The error component of this model can be decomposed as $\omega_{kit} = \mu_i + \theta_{it} + \varepsilon_{kjct}$. The element μ_i represents the component of student residual test scores that can be attributed to teacher i, once student characteristics have been taken into account.

Kane and Staiger (2008) and Chetty et al. (2014a) propose a method for the estimation of μ_i which relies on an empirical Bayes estimator. The empirical Bayes estimator is a best linear predictor of the random teacher effect in the achievement equation above. The basic idea of this approach is to multiply a noisy estimate of teacher value-added (e.g., the mean residual over all of a teacher?s students from a value-added regression) by an estimate of its reliability. Kane and Staiger (2008) use the ratio of signal variance to signal plus noise variance as a measure of reliability. As a result, less reliable estimates are shrunk back toward the mean.[44]

Estimation of teacher value-added requires student-level information on test scores and other individual characteristics, matched with identifiers of the teachers who taught each student over time. This type of information is not available to researchers for Wisconsin students. The necessity to use aggregate grade-subject level test scores data prevents me from applying the estimation approach presented above in a straightforward way. I now describe the available data and the procedure used to compute the measures of value-added used in the empirical analyses of this paper.

Achievement data for Wisconsin students is available at the grade-subject-school-year level for grades 4, 8 and 10 in the years 1999 to 2005, and for grades 3-8 and 10 in the years 2006 to 2014. Average standardized test scores are reported for mathematics, readings, and English-language-arts separately for each grade, school, and year. To estimate teacher value-added I use teacher assignment information to match test scores to the identifiers of the teachers assigned to a specific grade, subject, and school in each year. In order to measure teacher quality in a way that is not affected by possible changes in effort caused by Act 10, I estimate value-added using data on the years 2006-2011.

I estimate value-added adapting the procedure described by Kane and Staiger (2008). Specifically, teacher value-added is defined as the teacher effect (μ) in the equation

$$A_{gst} = \beta X_{gst} + \nu_{gst}, \text{ where } \nu_{gst} = \sum_{i \in J_{gst}} \mu_i + \epsilon_{gst}$$

where A_{gst} is average achievement in grade g, school s, and year t, and J_{gst} denotes the set teachers serving grade g in school s and in year t. The control variables X_{gst} include characteristics of the composition of students, including the share of female students, students by race and ethnicity, with limited English proficiency, with low socio-economic status, disabled, and migrant, and a set of school-year and grade fixed effects. The residual (ν_{gst}) can be decomposed into an aggregate teacher component, $\sum_{i \in J_{gst}} \mu_i$, whose elements μ_i are constant for each teacher over time, and an idiosyncratic component that varies across grades, schools, and over time ϵ_{gst}.

To obtain teacher fixed effects I follow Kane and Staiger (2008) and proceed as follows.

1. I estimate β using standard OLS, regressing achievement on the control variables described above;

2. I predict residuals $\hat{v}_{gst}$, and assign them to each teacher depending on her grade-school assignment in each year. This allows me to compute $\bar{v}_{it}$, the average residual for teacher i in year t across all grades taught (if more than one).

3. I use the residuals to compute the following quantities:

   - The variance of the teacher component ($\mu_{i(gst)}$) of the residuals, $\sigma^2_\mu = Cov(\bar{v}_{it}, \bar{v}_{it-1})$;
   - The variance of the idiosyncratic component (ϵ_{gst}) of the residuals, $\sigma^2_\epsilon = Var(v_{gst}) - \sigma^2_\mu - \sigma^2_\epsilon$.

[44] When value-added is used as a dependent variable in an empirical model, I do not apply the shrinkage factor as this would yield biased estimates of the parameters of the model.

4. I compute a average of the average residuals for each teachers, weighted by its precision:

$$\bar{v}_i = \sum_t w_{it}\bar{v}_{it} \qquad \text{, where } w_{it} = \frac{h_{it}}{\sum_t h_{it}} \text{ and}$$
$$h_{it} = \frac{n_{it}}{\sigma_\epsilon^2}$$

where n_{it} is the number of students in the grade and school teacher i is assigned to in year t.

5. Finally, I compute value-added as

$$VA_i = \bar{v}_i(\sigma_\mu^2 / Var(\bar{v}_i))$$

where $Var(\bar{v}_i) = \sigma_\mu^2 + (\sum_t h_{it})^{-1}$, $h_{it} = (\sigma_\theta^2 + \sigma_\epsilon^2/n_{it})$ represents the shrinkage factor, and captures the reliability of $\bar{v}_i$ as an estimate for μ_i.

I estimate value-added separately for each subject, and for teachers serving elementary schools (grades 1 to 5) and secondary schools (grades 6 to 12).

A few considerations on the identification of teacher value-added are in order. First, as in Kane and Staiger (2008) and Chetty et al. (2014a), identification of value-added relies teacher turnover at the school-grade level. To understand the design, suppose a high-value-added fourth grade teacher moves from school A to another school in 2012. Because of this change in the group of teachers, fourth graders in school A in 2012 will have lower-value-added teachers on average than the previous cohort of students in school A. If value-added estimates have predictive content, we would expect fourth grade test scores for the 2012 cohort to be lower on average than the previous cohort (Chetty et al., 2014a).

Second, value-added measures are available only for a subset of teachers. Value-added can be computed only for teachers of mathematics and reading, i.e. the subjects covered by standardized testing. The share of teachers with value-added is equal to 57 percent in 2008, 56 percent in 2010, 51 percent in 2012, and 44 percent in 2014 in salary-schedule districts, and to 59 percent in 2008, 58 percent in 2010, 53 percent in 2012, and 45 percent in 2014 in individual-salary districts (Figure A10).

One of the main limitations of my measure of teacher value-added based on aggregate achievement data is measurement error, which pushes the estimates around zero. Standard deviations of teacher and teacher by year effects are reported in Appendix Table A7 (column 1). The standard deviation of teacher effects varies from a minimum of 0.095 for elementary reading teachers to a maximum of 0.218 for eleentary mathematics teachers. These standard deviations are similar to the ones reported in Kane and Staiger (2008), which report values between 0.08 and 0.1 for estimates obtained from a model of student achievement that uses student fixed effects. Not surprisingly, the variance of teacher effects is larger when the shrinkage factor is not used (column 2).

I validate value-added estimates based on achievement data using a sample of math achievement data matched with teacher data from New York City for the years 2006-2010. I compute two time-invariant measures of value-added: one based on applying the above procedure to aggregate (grade-level) achievement data, and one using individual-level achievement data and following the procedure outlined by Kane and Staiger (2008). I include past test scores, an indicator for poverty and disability, gender, race, and ethnicity dummies, as well as grade and year fixed effects in the vector of controls X_{kt}. Figure A11 shows a binned scatterplot of the two measures of value-added. The relationship between the two measures is linear, and the slope of the relationship is equal to 1.09 (significant at 1 percent). Figure A12 shows a histogram of the distribution of the two measures. As anticipated, the distribution of the measure based on aggregate data is more concentrated around zero, with a standard deviation of 0.042 standard deviations of test scores, compared with a standard deviation of 0.146 for the measure based on individual-level student data.

Appendix E - Solving the District's Problem

The problem faced by the district is as follows (I drop the subscript j for simplicity):

$$\begin{aligned} &\max_{\{o_i\}_{i \in N}} \sum_{i=1}^{N} h_i o_i u_i \\ \text{s.t.} \quad &\sum_{i=1}^{N} h_i o_i w_i \leq B \\ &\sum_{i=1}^{N} h_i o_i \leq H \\ &o_i \in \{0,1\} \ \forall i = 1,..,N \end{aligned}$$

where $o_i = 1$ if an offer is made, h_{ij} is an indicator of whether teacher i accepts district j's offer, if one is made, u_i is the utility from hiring teacher i, w_i is wage, B is the budget constraint, and H is the maximum number of teachers which can be hired.

This is a linear programming problem which can be seen as a two-constraints version of the 0-1 knapsack problem. I solve it using the algorithm proposed by Martello and Toth (2003), which develops in the following steps.

1. Write the continuous relaxation (CR) of the problem, i.e. substitute the third constraint with the milder $0 \leq o_i \leq 1 \ \forall i$.

2. Re-write the CR problem as a function of a Lagrange multiplier (λ) on the second constraint (CR(λ)):

$$\begin{aligned} &\max_{\{o_i\}_{i \in N}} \sum_{i=1}^{N} h_i o_i (u_i - \lambda) + \lambda H \\ \text{s.t.} \quad &\sum_{i=1}^{N} h_i o_i w_i \leq B \\ &0 \leq o_i \leq 1 \ \forall i = 1,..,N \end{aligned}$$

3. Solve the CR(λ) problem as in Dantzig (1957). The solution to this problem, o^{c^*}, is as follows:

$$o^{c^*}(\lambda) = \begin{cases} 1 & \text{if } i < s(\lambda) \\ c - \frac{\sum_{j=1}^{i-1} w_j}{w_i} & \text{if } i = s(\lambda) \text{ and } h_i(u_i - \lambda) \geq 0 \\ 0 \text{ if } i = s(\lambda) & \text{and } h_i(u_i - \lambda) < 0 \text{ or } i > s(\lambda) \end{cases} \tag{24}$$

where teachers are sorted so that $h_i(u_i - \lambda)/w_i \geq h_{i+1}(u_{i+1} - \lambda)/w_{i+1}$, and $s(\lambda)$ represents the "critical" teacher, i.e. $s(\lambda = \min\{i : \sum_{j=1}^{i} w_j h_j > B \text{ or } h_i(u_i - \lambda) \leq 0\}$.

4. For a given λ, define the solution to the discrete choice model as $o^*(\lambda) = \lfloor o^{c^*}(\lambda) \rfloor$.
5. Select the optimal λ^* as follows:
    (a) Construct a set S of admissible levels of λ. As shown by Martello and Toth (2003), this includes: a) $\lambda = 0$; b) $\lambda = u_j \; \forall i$; c) $\lambda = (u_j w_i - u_i w_j)/(w_j - w_i) \; \forall i < j$ and such that $\lambda > 0$.
    (b) For each of these admissible levels, compute the value of the relaxed budget constraint: $R(\lambda) = \sum_{i=1}^{s(\lambda)-1} h_i + o^{c^*}_{s(\lambda)}(\lambda) h_{s(\lambda)}$
    (c) Select the median value of the elements of S, called λ^M.
    (d) If $R(\lambda) = H$, then $\lambda^* = \lambda^m$.
    (e) If $R(\lambda) > H$, then remove λ^m from S, and reiterate from (c).

The solution to the problem is then given by $o^*(\lambda^*)$. It should be noted that this procedure selects only one value of λ^*, and therefore yields a unique solution to the problem. In principle, however, all λ satisfying $R(\lambda) = H$ are optimal, which would give rise to multiple optimal solutions to the problem. Since, as shown by Martello and Toth (2003), $R(\lambda)$ is a non-increasing function of λ, the only case in which this can happen is if the function $R(\lambda)$ is flat and equal to H over an interval $[\underline{\lambda}, \overline{\lambda}]$. In this case, all λs in this interval would give rise to optimal solutions. It should be noted, however, that these λs will all be relatively close to each other, and virtually yield the same solution to the problem.