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Skill shortages: demographic change, educational choices and matching in the VET market.*

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- Preliminary Version -

Abstract

In recent years firms in many European countries report increasing difficulties to fill their vacancies with skilled workers. In Germany, the number of individuals who enter into firm-based vocational training (VET) has decreased by 17% between 2009 and 2021, which is likely to result in further shortages of qualified workers in the future. In this paper, we study the main mechanisms behind this negative trend in VET from two perspectives. First, we use data on VET matches and school-leavers by education to show that the main driver of the observed pattern is demographic change. Changes in young adults' interests in VET play a smaller role. Without demographic change, the decrease in matches between 2009 and 2021 would have been only 6.9%, while constant educational choices would improve the observed decrease by only 3 percentage points. Second, we study matching in the VET market and the role of regional and occupational mismatches by using disaggregated data on matches, applicants and vacancies by occupations and districts. This is important since the aggregate trends hide potential mismatch between vacancies and applicants by occupation and district, which we show are increasing over time. Moreover, by estimating empirical matching functions, we are able to study the changes in matching efficiency holding the numbers of applicants and vacancies constant. We find that while relatively stable before 2019, matching efficiency drops sharply during the Covid crisis. Between 2013 and 2021, 19% of the observed decline in matches stems from the worsening matching efficiency.

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1 Introduction

Skilled workers are currently lacking in the labor market in several European countries. In Germany, these skill shortages can be directly linked to a lack of workers who obtained firm-based vocational education and training (VET). Firm-based VET is an important pillar of training the workforce in Germany. Further, VET contributes to a smooth school-to-work transition, especially for middle- and low-skilled individuals. However, the strong decrease in the number of newly signed apprenticeship contracts suggests that VET is losing importance over time. Between 2009 and 2021 the number of newly signed contracts decreased by 16% from around 56,000 to 47,000. This is likely to result in further shortages of qualified workers in the future and thus challenges the economy as a whole.

The VET market functions as a specific labor market, in which firm post apprenticeship vacancies in a specific occupation and school leavers apply to these vacancies. Since signed contracts are the result of how applicants and vacancies find together, matches cannot be studied in absence of its two main components: applicants and vacancies. While the number of applicants has exceeded the number of vacancies throughout the the entire period between 2009 and 2021, there was a much stronger decline in applicants than in vacancies (11% vs. 5%). Given that the decline in matches is beyond the decline in applicants and vacancies, the interaction of supply-side, demand-side and changes in matching may be behind this development.

In this paper, we thus evaluate the importance of supply-side and demand-side mechanisms together with changes in matching in explaining the decline in started apprenticeships. First, we use data on VET matches and school leavers by education between 2009 and 2021 to analyze the importance of three supply-side mechanisms, assuming a constant number of vacancies and matching efficiency over time: (i) demographic change, (ii) change in educational attainment and (iii) changes in the transition rates into VET by education. While the first one yields smaller cohort sizes over time, the second and third mechanisms have ambiguous effects on the number of VET matches. For instance, we observe that over the years, an increasing share of school leavers obtains a high school degree and may thus decide for university instead of VET. However, we also observe that within those with a higher school degree, a larger share ends up in a VET than before. When we quantify the impact of each factor we find that demographic change is the most important driver. If the number of school leavers was constant from 2009 onwards, there would have been a decrease of 9% in matches, instead of the observed decline of 16%. Leaving the educational attainment and the transition rates into VET constant from 2009 onwards would both yield a decrease of 13%. Comparing these overall decreases to the pre-Covid period (2009-19), we see that changes in educational attainment affect the decrease in matches stronger than changes in transition rates into VET, which even would have led to an increasing number of matches until 2019.

We next study the evolution of the matches through the lens of a matching function. In particular, we first study how tightness (vacancies/applicants) evolved on the aggregate and within occupations and geographical areas. To this end, we use data on matched, applicants and vacancies between 2013 and 2021 at the 2-digit occupational x district level. While aggregate tightness is approaches one at the end of 2021, zooming into occupations and districts we show that mismatch, measured as the standard deviation of the distribution of tightness at this disaggregated level, has increased (from 0.12 to 0.16 between 2013 and 2021). This suggests that some regions and occupations face higher problems than others and these differences became stronger over time. While this macro mismatch in the occupational and regional distributions of applicants and vacancies is one of the sources of the inefficiency, the other comes from unobserved differences in matching efficiency. To recover this matching efficiency, we estimate empirical matching functions by occupation and district between 2013 and 2021. Our results show that matching efficiency has worsened over the observed period as well, with notable drops in the Covid crisis.

Last, we evaluate the relative importance of the change in tightness and in matching efficiency. The findings of our counterfactual analysis suggest that if the matching efficiency stayed on its 2013 level, we would observe a decrease of 8% until 2021 and even a slight increase of about 1% until 2019. With a constant number of applicants and vacancies from 2013 onwards, the decrease would only be 2% until 2021, with almost no decrease of only 1% until the start of the Covid pandemic.

Our paper contributes to various strands of the literature. First, the literature on matching with frictions which estimates empirical matching functions to identify changes in matching efficiency (Pissarides, 2011; Yashiv, 2007; Rogerson et al., 2005; Petrongolo and Pissarides, 2001). More specifically, we focus on matching efficiency in 1) local markets (states), as Manning and Petrongolo (2017); Dauth et al. (2016) and 2) occupations as Fedorets et al. (2017) whose study addresses matching spillovers between occupational labour markets. Our paper contributes to this literature by shedding light on the matching in a market with a specific timing, the vocational market, in which matching occurs over a fixed period of time, with a yearly starting date of the apprenticeship.

By focusing on the VET market, we naturally contribute to the literature on the matching in the VET market, which is scarce. Muehlemann et al. (2020) study how new contracts in the vocational market relate to business cycle conditions. While these authors provide descriptive results on the evolution of the matching based on data on unfilled vacancies and unsuccessful applicants, they do not directly estimate matching functions to provide the elasticities of applicants and vacancies. To the best of our knowledge, we are the first to estimate matching functions in the VET market.

Our results on the effect of the Covid crisis on the matching in the VET market also contribute to the literature on the consequences of entering the labor market during an economic downturn (Schwandt and von Wachter, 2019; Cockx and Ghirelli, 2016; Oreopoulos et al., 2012; Kahn, 2010). These studies focus mostly on the year of graduation (from high-school or university) and find negative short-term and long-term effect. Our results show that such negative effects can be observed in the VET market as well, as we show that matching efficiency decreases in the years of the Covid crisis.

2 Data

Our main data on the VET market comes from the Federal Institute for Vocational Education and Training (BiBB) in Germany. The BiBB reports all apprenticeship contracts reported to the chambers in Germany and thus gives the entire picture of the signed apprenticeship contracts in Germany. A particular feature of the VET market is the fixed timing structure of the apprenticeship year. While apprenticeships traditionally start in August or September, registration by applicants and vacancy posting starts as early as in October of the previous year. Contracts can be signed at any point. For each apprenticeship year the BiBB data reports the cumulated number of signed contracts as of 30th September of each apprenticeship year. The Bibb constructs the demand and supply in the VET market by adding information on unsuccessful applicants and unfilled vacancies from the Federal Employment Agency (BA), which has this information from the counselling activities.¹

First, we use yearly data on the total number of signed apprenticeship contracts (matches) between 2009 and 2021 by education.² Second, to study local labor markets we use disaggregated data on the level of federal states (16), districts (156 Arbeitsagenturbezirke, AA) and occupations

¹Note however, that the BA can only provide this information if individuals and firms participate in the counselling activities. Therefor, this data does not contain the universe of all applicants and vacancies in the apprenticeship market because some individuals and firms may search independently but may not end up with finding a suitable position or candidate.

²After primary school, students are tracked into different school types that translate into different educational degrees. The data contains information on apprentices' educational degree, i.e. 1) no school degree 2) low degree 2) intermediary degree and 4) upper-secondary degree (University entry certificate)

(35 2-digit occupations) level. The disagreggated data is available from 2013 onwards.

In addition, we use data on the numbers of school leavers of each educational degree over time, both aggregated and by district. This data gives us the number of school leavers in each year who have obtained a certain degree (or those who are leaving the educational system without a degree). This information comes from the Federal Statistical Office.

Finally, we use micro data on all applicants who register with the Federal Employment Agency (BA). This data contains spell-wise information about the region of the applicant, the aspired occupation and whether they successfully entered VET.

3 Developments in the VET market

Figure 1 shows the developments in the VET market since 2009. Panel (a) shows the evolution of matches in Germany. From 2009 to 2021, matches decreased by 16% with a strong decline during the Covid crisis. Panel (b) shows the evolution of applicants and vacancies. Although the number applicants is generally larger than the number of vacancies, over time applicants decreased by much more than vacancies did (11.4% and 4.9%, respectively). Given that the decline in matches exceeds the decline in both applicants and vacancies matching itself, i.e. applicants and vacancies finding together, may have changed. As matching occurs at the occupational and regional level, this aggregate representation may mask important heterogeneities. E.g. there may be a mismatch in the types of occupations that individuals apply to and where firms are searching for candidates such that there may be growing difficulties to match applicants to vacancies in general. The same argument holds on the spatial level. In addition, matching itself may have become less efficient over time.



Notes: This figure shows the evolution of the total number of signed apprenticeship contracts as of Septmber 30th each year, together with the numbers of applicants and vacancies

Figure 1: Evolution of the VET matches

Given the shortages of skilled labor in Germany, it is of key importance to understand the mechanisms behind the observed decrease in new VET contracts and assess the relative importance of each channel. As a first step, we present evidence of three supply-side mechanisms which may explain the trends in 1. Here we discuss the impact of demographic change, changes in the take-up of different levels of education and changes in VET take-up of differently educated groups. We then focus on how mismatch in terms of differences in occupational distributions between applicants and vacancies within regions where matching occurs (districts) evolves over time. Base on these findings we estimate empirical matching functions which allow us to recover the changes in matching efficiency over time.

4 Supply-side mechanisms (Apprentices)

Depending on their level of education, school leavers can choose among different alternative paths that they want to pursue after graduating. Therefore the number of (potential) applicants depends first, on the number of school leavers. Second, the number of applicants depends on an individual's choice for the level of education as this determines the school-to-work transition, e.g. whether education is more practically oriented or whether the school track provides more extensive general education that also allows students to enter (applied) universities. Third, it depends on an individual's preference for entering VET versus continuing (higher and/or tertiary)

education. In the following we study to what extent these mechanisms can explain the overall decrease in matches, assuming that matching has stayed constant.

4.1 Demographic change

VET is typically the first step in individuals' transition from school to work, hence in the first years after leaving school or at a relatively young age. Panel (a) of Figure 2 shows the evolution of (i) matches and (ii) the population size of the 15 to 24 age group. Both develop in the same way (correlation of 0.83) and are decreasing over time. In addition panel (b) shows that the number of school leavers also follows matches closely (correlation of 0.78). Moreover, both school leavers and matches decline most during the crisis years of 2008/2009 and 2019/2020, likely due to students deciding to stay in school longer in times of economic uncertainty.



Notes: This figures shows the number of BiBB matches (left y-axis) and the number of individuals in the age-population of 15-24 (right y-axis in panel (a)) and the total number of school leavers (right y-axis in panel (b)).

Figure 2: Demographic change and VET contracts

Given our interest in studying changes in education, we also split matches by educational degrees to compare them with the number of school leavers by different educational degrees. Panels (a)-(d) of figure 3 distinguishes between no degree, low degree, intermediate degree and upper secondary degree. First, the evolution of the different educational groups is different from the patterns observed for overall school leavers. In particular, the very low-skilled (individuals with no school degree) exhibit a U-shaped evolution before the Covid crisis, while the high-skilled (individuals who obtain a high-school degree and could enter university) are increasing over time.

Second, more importantly, we observe that the patterns of school leavers by education are closely followed by the number of signed apprenticeship contracts by applicants' level of education. This points to the fact that demographic change is driving a large part of the decrease in matches.³



Notes: This figure shows the number of school leavers by education (left y-axis) and the numbers of matches of apprentices with the corresponding levels of education.

Figure 3: Demographic change and VET contracts by school degree

³In the appendix, we study these changes according to age as well. In panels (a), (b) and (c) of Figure 16 we show matches split by age groups which correspond to the population age groups. This figure shows that while the decrease in total matches between 2008 and 2020 has been substantial, it has been observed in all age groups, and the number of matches follows closely the pattern of population size.

4.2 Changes in the decision to take up secondary education and educational composition of VET

In the German system, the entry into VET is possible with different educational degrees and ages. However, it typically marks the first entry into the labor market. Depending on an individual's school degree, the number of alternatives to VET as well as the chances to find a VET positing are likely to vary. After primary education, for secondary education, individuals are tracked into different school types. The tracks differ in their duration, difficulty and the final degrees. Because each federal state is responsible for its school policies, there are also variations between states. Overall, the tracks can be classified into low, medium and high track, translating into their final degrees, i.e. low or basic, intermediate and upper secondary degree. Given that the choice for one of those tracks is made at the age of 10-12, it is likely that individuals have not yet decided for or against VET at this stage. As VET does not require any school degree, all students in their last school year can decide to apply for VET (also in case they have already fulfilled the compulsory schooling time and might drop out from school). Note, however that most positions require some school leaving certificate. Alternatively, students who finish a track with sufficiently good grades can continue schooling to obtain a higher school degree (e.g. obtaining an upper secondary degree that entitles individuals to commence academic studies after an intermediate degree). The noticeable number of matches above the age of 20 years in panel c of figure 16 in the appendix points out that some individuals do not directly enter VET after finishing school. They might be drop-outs from VET or from university, come from various transition programs, or might have already obtained a vocational degree or university degree before. Some individuals may have gained some work experience before they have decided to apply for VET.

We show the number of contracts by education group over time in Figure 4. Looking at the patterns in Figure 4, an interesting picture emerges. Overall, the largest group of VET matches has a medium school degree. While the number of contracts signed by individuals with a high degree (corresponding to a high-school degree which allows individuals to join university) has increased over time, the number of those holding an intermediary or basic degree has decreased. The number of VET matches without any school degree seems to play a minor role, which is also related to the relative small number of school leavers without degree overall (see Panel (d) of Figure 3).



Notes: This figure shows the number of signed contracts by the highest education of the apprentices. Figure 4: VET matches by school degree

While informative, this figure confounds two different factors that may be changing over time. To illustrate this, consider the total matches in year t, y_t , and total matches in year education group e in year t, y_{et} , to be

$$y_t = \sum_{e=1}^n y_{et} = \sum_{e=1}^n w_{et} N_{et} = \sum_{e=1}^n w_{et} h_{et} N_t$$
(1)

where N_{et} is the total number of school leavers with education level e in year t and w_{et} is the share of contracts signed in year t of individuals with education e of total school leavers with education e. h_{et} is the share of each education group in total school leavers at time t, N_t .

Following Equation (1), the matches in Figure 4 can be decomposed into two main objects of interest: The first one is the share of number of school leavers in each educational group by year (h_{et}), and the second one is the transition rate into VET by degree, w_{et} computed by the number of matches over school leavers in each educational group. We show in the left panel of Figure 5 that the share with a low degree has been decreasing over time, whereas the share with a medium or high degree is slightly increasing. The second margin that drives the evolution of the number of matches into VET by school degree are the transition rates w_{et} in panel (b) of Figure 5. From this we can conclude two main findings. First, the transition rates into VET vary with educational degree. Considering the different outside options by degree, this is not surprising. However, together with the fact that the educational composition changes, this effects the number of matches: As the group with a low degree has the highest entry rates overall and their share is decreasing over time, this results into a decrease in matches. Note that our measure divides VET matches by school leavers. Hence, the entry rates above 1 during the financial crisis reflect the fact that low skilled individuals had to delay their entry into VET as they did not find an apprenticeship.

Second, the right panel of figure 5 also shows changes in the transition rates: For school leavers with a high degree, it is increasing, which - in combination with their increasing share among all school leavers - imply an increase in matches. Those with a medium degree tend to start a VET less often, which can be driven by other options like further schooling or school-based VET becoming more attractive. Although still being the main choice after leaving school with a low school degree, the transition rate is also decreasing here, which could be driven by problems in finding an apprenticeship.



Figure 5: Shares of school degrees and entry rates into VET

4.3 Evaluation of the different mechanisms

To understand how much each factor contributes to the change in contracts by education, we perform four counterfactual exercises, assuming that the rates of matching stay constant over time (any changes in composition do not affect the rate of matching). In the first exercise, we fix the shares of each the school leavers in each education group who get a VET contract to

the 2009 level and let the share of school leavers by education (h_{et}) vary. We then compute the counterfactual evolution of the VET market, by using the actual evolution of school leavers (N_t) between 2009 and 2021. The second exercise keeps the 2009 shares of educational groups fixed while we use the actual number of school leavers (N_t) and entry rates by education (w_{et}) . We repeat both exercises while keeping the total number of school leavers at the 2009 level and thus assuming that there was no demographic change. We summarize the different counterfactual exercises and their corresponding equations for our counterfactual matches y_{et}^{CF} in Table 1.

Counterfactual	Equation
CF 1.1: No changes in entry rates into VET	$y_t^{CF1.1} = \sum_{e=1}^n w_{e,2009} h_{et} N_t$
CF 1.2: No changes in educational composition	$y_t^{CF1.2} = \sum_{e=1}^{n} w_{et} h_{e,2009} N_t$
CF 1.3: No demographic change	$y_t^{CF1.3} = \sum_{e=1}^n w_{et} h_{et} N_{2009}$
CF 1.4: No changes in entry rates into VET and education	$y_t^{CF1.4} = \sum_{e=1}^{n} w_{e,2009} h_{e,2009} N_t$

Table 1: Counterfactuals

We then show the original time series together with the counterfactual time series 1.1 - 1.3 in Figure 6. From 2009-2021, the observed decrease in matches was 16%. Without demographic changes, this decrease would roughly half to 9%. Changes only in educational composition as well as changes only in the entry rates into VET only have a minor and almost similar impact until 2021 (12%).



Figure 6: Counterfactual matches

	09-19	09-21	13-19	13-21
Actual	8.47	16.37	3.44	11.77
1.1 No demographic Δ	4.00	8.83	-1.58	3.52
1.2 No Δ in educ. composition	4.90	12.88	2.32	10.58
1.3 No Δ in entry rate in VET	9.20	12.62	6.21	9.94
1.4 No Δ in educ. and entry rate in VET	4.66	8.28	4.94	8.55

Table 2: Decrease in matches for actual and counterfactual matches

Figure 7 shows the counterfactual time series 1.1 together with 1.4. The results show that the decision for a school degree and the entry into VET are highly correlated.



Figure 7: Counterfactual matches

Table 2 shows the results for different time periods. It can be seen that from 2009 until before the Covid pandemic, the changes in educational composition play a much bigger role: If the educational composition had remained constant from 2013 onwards, matches would have been decreased by 5%, which is roughly half of the actually observed decrease in matches of 9% from 2009 until 2019. The results also show that without a change in entry rates into VET there would have been even slightly less matches until 2019, indicating either increasing interest in VET among some educational groups or improving matching.

When considering the whole time period until 2021, it can be seen that both the counterfactual scenario of no demographic change and the scenario of no change in education and entry rate in

VET would roughly halfen the observed decrease of about 16 percent to about 8-9 percent.

In order to make this set of counterfactuals comparable to a later set which contains only the time period 2013-2021, we also report the results from 2013 onwards in column 3 and 4. Considering the time period 2013-2021, demographic change is again the most important driver of the decrease in matches. Before the start of the Covid pandemic, the entry rate into VET increased.

From comparing rows 2, 3 and 4, it can be seen that the changes in school degrees and the changes in the entry rates are correlated. When holding both the educational composition and the entry rates constant on their 2009 level, we would have a scenario with more low educated and less high educated school leavers together with higher entry rates for low and medium educated and lower entry rates for high educated. Both the demographic change and the change in education and VET entry rate together thus explain about half of the total decrease each.

However, the changes in educational composition and the entry rates into VET could stem from different mechanisms theirselves.

One way could be that firms prefer applicants with a high school degree over applicants with a low or medium degree. Thus, the declining entry rates into VET for low (and medium) skilled individuals might reflect problems to find an apprenticeship. The trend towards higher education and the increasing VET-entry rate suggest that individuals might want to improve their job perspectives in the VET market rather than being more interested in other career options (e.g. university studies).

Another explanation could be that, school leavers with a high degree tend to choose VET apprenticeships in different occupations than those with a low school degree. This could result in more (high skilled) applicants in specific occupations and thus lower chances to find apprenticeships for the high skilled, and on the other hand less (low skilled) applicants in other occupations with better chances.

In order to account for the mismatch between applicants and vacancies and matching problems, we next describe matching in the VET market in more detail.

5 Matching in the VET market

We have shown the relative importance of three supply-side factors, assuming that matching has stayed constant over the period that we consider. However, it is important to consider both sides of the market, since obtaining a match in VET is a process similar to matching in any other labor market: firms post vacancies and applicants apply for them. For most, this is the first match in the labor market (VET occurs at a training firm and the literature has shown that between two-thirds and three-quarters of all successful VET graduates remain in their training firm after completing their training, see e.g. Jansen et al. (2015); Leber (2023)) and can have long-lasting consequences for their future career. We thus next analyze the matching in this particular market by looking at the developments of applicants and vacancies and the potential mismatches in terms of occupations and regions within Germany.

5.1 Simple model of matching with disaggregation

We have shown the relative importance of three supply-side factors, assuming that matching has stayed constant over the period that we consider. However, obtaining a match in VET is a process similar to matching in any other labor market: firms post vacancies and applicants apply for them. Thus changes in matching itself contributes to the decline in matches. In addition, for many young individuals the VET market is the labor market where their first match occurs, with long-lasting consequences for their future employment biographies. In the next step we thus analyze the matching in this particular market by looking not only at the developments of applicants and vacancies but also potential mismatches on the level of occupations and regions within Germany.

In a labor market, we assume a Cobb-Douglas matching function with constant returns to scale:

$$M = EA^{\theta}V^{1-\theta} \tag{2}$$

where A are applicants, V are vacancies E is the matching efficiency. An alternative parametrization of (2) can be achieved using the labor market tightness, i.e. the ratio of vacancies and applicants, as a second argument instead of vacancies.

$$M = E \cdot \left(\frac{V}{A}\right)^{1-\theta} \cdot A. \tag{3}$$

Considering the different input factors, we see that the number of matches increases in both input

factors, independently from the chosen parametrization.

Now let us assume that the overall market consists of n disaggregated labor markets. We denote cell-wise matches of labor market i by

$$M_i = E_i(\alpha_i A)^{\theta} (\beta_i V)^{1-\theta},$$

where $\alpha = (\alpha_1, ..., \alpha_N)$ and $\beta = (\beta_1, ..., \beta_N)$ represent the distribution of applicants and vacancies, respectively, over the cells (i.e., labor markets).

The total number of matches is then given by

$$M = \sum_{i=1}^{n} E_i (\alpha_i A)^{\theta} (\beta_i V)^{1-\theta} = \underbrace{A^{\theta} V^{1-\theta}}_{1} \underbrace{\left(\sum_{i=1}^{n} E_i \alpha_i^{\theta} \beta_i^{1-\theta}\right)}_{2}.$$
(4)

If we have the same matching efficiency in each labor market, $E_i \equiv E$, we can rewrite (4) as

$$M = \sum_{i=1}^{n} E_i (\alpha_i A)^{\theta} (\beta_i V)^{1-\theta} = \underbrace{A^{\theta} V^{1-\theta}}_{1} \underbrace{\left(\sum_{i=1}^{n} \alpha_i^{\theta} \beta_i^{1-\theta}\right)}_{2} \underbrace{E}_{3}.$$
(5)

The first factor in (4) shows the impact of the overall tightness on the number of matches. If A = V, it is independent of θ . In the case A > V, we see that the number of matches increase as θ increases towards 1. For V > A the number of matches increases as θ decreases towards 0, leaving the other parameters constant.

In the special case of $E_i \equiv E$, we see that the second factor in (5) describes how mismatch shrinks down the number of matches, as this factor is smaller or equal than 1, and equals 1 iff $\alpha_i = \beta_i$, i.e. if the distribution of applicants among cells is equal to the distribution of vacancies among cells. The matching efficiency E thus shrinks down the number of matches furthermore if E < 1.

In the general case of different matching efficiencies E_i , we see by formula (4), that there is an interaction between cell-wise mismatch and matching efficiency: The shrinkage of the total number of matches by a *small* cell-wise matching efficiency E_j is bigger if it occurs in a relatively *large* cell, i.e. in a cell with a large share of applicants and/or vacancies, i.e. if α_j and/or β_j are large (whereas θ drives their relative contribution and is equal if $\theta = 0.5$, α_j matters more if $\theta > 0.5$ etc.).

As our data are disaggregated both by occupations and by districts, we might rewrite (4) as

$$M = \sum_{d} \sum_{o} E_{od} (\alpha_{o|d} \cdot \alpha_{d} A)^{\theta} (\beta_{o|d} \cdot \beta_{d} V)^{1-\theta} = \sum_{d} \sum_{o} E_{od} (\alpha_{d|o} \cdot \alpha_{o} A)^{\theta} (\beta_{d|o} \cdot \beta_{o} V)^{1-\theta}.$$
 (6)

Here, α_d and β_d describe the (unconditional) regional distribution of applicants and vacancies, respectively. Analogously, α_o and β_o describe the regional distribution of applicants and vacancies. The terms $\alpha_{o|d}$, $\beta_{o|d}$, $\alpha_{d|o}$ and $\beta_{d|o}$ describe the respective conditional distributions.

Using the tightness as a second input factor instead of vacancies according to (3), equation (6) can be rewritten as

$$M = \sum_{d} \sum_{o} E_{od} \left(\frac{\beta_{o|d} \cdot \beta_d V}{\alpha_{o|d} \cdot \alpha_d A} \right)^{1-\theta} \cdot (\alpha_{o|d} \cdot \alpha_d A) = \sum_{d} \sum_{o} E_{od} \left(\frac{\beta_{d|o} \cdot \beta_o V}{\alpha_{d|o} \cdot \alpha_o A} \right)^{1-\theta} \cdot (\alpha_{d|o} \cdot \alpha_o A).$$
(7)

In the next subsections, we will study the different input factors in more detail.

5.2 Labor Market Tightness

Figure 8 shows the evolution of the tightness, i.e. vacancies over applicants, on the *aggregate level* over time. It can be seen that throughout our observation period, the number of applicants exceeds the number of available vacancies, but given a stronger decline in applicants, this gap almost closes on an aggregate level. However, this graph hides variation on the local (disaggregated) level where matching is likely to occur. In columns 2-6 of table 3, we show the standard deviations of tightness on different aggregation levels, moving to finer aggregation levels. First, moving to finer aggregation levels, the standard deviations increase. This provides evidence that matching occurs at a fine aggregation level, i.e. on the level of occupation x district. Second, the standard deviations is increasing over time at each aggregation level. This indicates that regions and occupations evolve heterogeneously and that there are some occupation x region cells with high excess of either applicants and vacancies besides the overall improving tightness.



Figure 8: Tightness in Germany over time

Overall Tightness		Stand	ard De	eviatio	n of Tightnes	s across:	
		for Germany	States	AA	Occs	StatesxOccs	AAxOccs
	2012/13	.919	.060	.073	.066	.096	.124
	2014/15	.935	.061	.074	.071	.102	.128
	2016/17	.948	.067	.081	.069	.106	.137
	2018/19	.966	.071	.087	.066	.107	.140
	2019/20	.966	.075	.095	.081	.123	.160
	2020/21	.991	.074	.096	.085	.123	.164

Table 3: Changes in tightness over time

5.3 Regional and occupational distribution

We have seen that the ratio of vacancies and applicants evolves heterogeneously across regions and occupations over time. A quantitative proof therefore can be given by studying the evolution of the distribution of applicants and vacancies given in equation (6). By definition, there are four different distributions for each applicants and vacancies: over occupations and over regions, unconditional and conditional. As the unconditional distribution over occupations consists of o = 35 values (one for each occupations) and the unconditional distribution over districts consists of even d = 153 values (for each district), it is complicated to give a comprehensive but short overview. A quantitative measure for differences between two distributions is the *Kullback-Leibler*



Figure 9: Changes in unconditional dispersions

Divergence or KL divergence, see Kullback and Leibler (1951). For two discrete distributions p and q defined on the same set of values, the KL divergence of distribution p to q is given by

$$D_{KL}(p|q) = \sum_{k=1}^{K} p_k \log\left(\frac{p_k}{q_k}\right).$$

By comparing the unconditional distributions for different years, we can show that statistically significant changes occur over time, indicating that both the importance of the different occupations and the size of the district change over time. Figure 9 gives a graphical overview of this analysis: In the upper panel, we study changes in the unconditional distributions of regions, for vacancies (left) and for applicants (right). Analogously, the lower panel shows the changes in the unconditional distributions of occupations. In each graph, the orange lines show the KL divergence from each year's distribution to the distribution from 2013, the first year in our observation period. The green line shows the KL divergences to the previous year each. There are two main findings: First, there are significant changes in the distributions both between occupations and between district going on for each year. Second, these changes were strongest in the Covid pandemic. Another set of graphs in Figure 21 in the appendix shows that also when studying changes in the conditional distributions, the changes between the current distribution and the distribution in the previous year are still significant in many cases, in particular for occupations by district.

5.4 Matching efficiency

Next, we study the role of matching by fixing the number of applicants and vacancies. We estimate the following empirical matching function:

$$m_{odt} = c + \theta_1 v_{odt} + \theta_2 a_{odt} + f_o + f_d + f_t + \varepsilon_{odt}$$

$$\tag{8}$$

where m_{odt} is the log of matches, v_{odt} is the log of vacancies, a_{odt} is the log of applicants, for an occupation o, in district d and in year t. f_o are occupation fixed effects (FE), f_d district FE and f_t year FE.

In order to check whether the educational composition in an occupation x district changes the matching, we optionally include the shares of three educational groups in the matching equation:

$$m_{odt} = c + \theta_1 v_{odt} + \theta_2 a_{odt} + \gamma_1 \mathsf{Educ}_{1odt} + \gamma_2 \mathsf{Educ}_{2odt} + \gamma_3 \mathsf{Educ}_3 + f_o + f_d + f_t + \varepsilon_{odt}$$
(9)

Here, $Educ_1$, $Educ_2$ and $Educ_3$ represent the share of applicants with no school degree, low school degree and a medium school degree, respectively. Together with the share of applicants with a high school degree, these sum up to 1 within each occupation x district.

	(1)	(2)			
VARIABLES	Log Matches	Log Matches			
	• • • • • • • • • • • •	• • • • • • • • • • •			
Log Applicants	0.475***	0.477***			
	(0.00955)	(0.00957)			
Log Vacancies	0.557***	0.557***			
	(0.00925)	(0.00925)			
Share Educ 1		-0.00902			
		(0.0108)			
Share Educ 2		-0.0349***			
		(0.00521)			
Share Educ 3		-0.00203			
		(0.00377)			
Constant	-0.438***	-0.436***			
	(0.0131)	(0.0131)			
Observations	37,485	37,485			
R-squared	0.996	0.996			
Year FE	Yes	Yes			
AA District FE	Yes	Yes			
Occ FE	Yes	Yes			
Pseudo R2	0.996	0.996			
F	62842	62022			
Wald Test	chi2(194) = 57.76				
	Prob > chi2	= 1.0000			
Robust standard errors in parentheses					

Robust standard errors in parentneses *** p<0.01, ** p<0.05, * p<0.1

Table 4: OLS Results

Table 4 reports the OLS estimates of the empirical matching function. Interestingly, including the educational shares of applicants does not change the estimates significantly, indicating that matching and education are not significantly correlated. Considering their estimates in column 2, we see that all estimates have a negative sign, i.e. a high share of the left-out category with a high school degree has the best impact on matching. However, the group with a medium school degree (Educ₃) has not significantly lower matching chances. The only significant estimate is those for the share of applicants with a low school degree (Educ₂). The estimate for the group with no school degree is also negative, but smaller in absolute values and insignificant. Overall, the results show that vacancies affect the number of matches more than applicants: An increase of vacancies by 1% is associated with an 0.56% increase in matches, whereas an increase in applicants by 1% corresponds to an increase in matches by 0.48%. The Year FE from the left



Figure 10: Year FE

column in figure 10 show that matching efficiency became slightly worse from 2013 until 2019, but then sharply decreased in the first year of the Covid pandemic, followed by a weak and insignificant increase in 2021.

Figure 17 in the appendix shows the occupational FE from column 1. As including the educational shares does not yield significantly different estimates, we furthermore only consider the first specification in equation 8.

In order to quantify the impact of the changes in the tightness, mismatch and matching efficiency, we perform two additional counterfactual exercises. These are based on estimation results, but however Figure 18 in the Appendix proves that the fit overall is very precise.

We have studied how different mechanisms on the supply-side mechanisms affect matches when not considering the number of vacancies matching efficiency in the first set of counterfactual exercises. Next, we study how the number of vacancies and their relationship to applicants affect the number of matches. Therefore, we consider different counterfactual scenarios where applicants are taken as given and vacancies vary.

The tightness can serve as another second input factor besides applicants. Thus, we consider in the first exercise (V1) how matches would change if there was no change in the tightness. In contrast, exercise two (V2) assumes the extreme case where tightness is equal to one in each occupation x district over the whole observation period. It is not clear ex ante how matches would evolve in these scenarios: First, we saw that the aggregated tightness tends more and more towards

1, but the variation in the disaggregated tightness also increases over time. Second, depending on the estimated elasticities and the different magnitudes of the FE between occupations and districts, different values of the tightness rather than 1 might yield to even more matches overall. In the first parametrization of the matching function, the vacancies appear as the second input factor besides applicants. In the third exercise (V3), we assume the overall number of vacancies to be constant on its 2013 level. Differences in the number of vacancies per district x occupations are incorporated by the changes in the observed distribution over district and occupation. Out prediction would be a higher number of matches than actually observed, as the total number of vacancies was decreasing over time. However, the magnitude of this difference is driven by changes in their distribution and changes in the matching efficiency.

In comparison, exercise four (V4) assumes a constant number of vacancies in each occupation x district. Also here, we would assume a higher number of matches overall through vacancies' overall decrease. But as the disaggregated evolution of vacancies is hidden in the overall picture, the magnitude depends again on the actually observed changes in vacancies' distribution and changes in the matching efficiency. Table 5 summarizes the computation of the counterfactual vacancies in these exercises and Figure 11 gives a graphical overview. In Table 6, we report the decrease compared to the observed matches within two time periods, before the start of the Covid pandemic (2019) and in the last observed year (2021).

Further counterfactual exercises are shown in the appendix. Related to the concept of tightness, one can think that the balance between the distribution of applicants and vacancies among occupations and applicants affects matches. We thus assume in exercise five (V5) that the distribution of vacancies across districts and regions was exactly similar to those of applicants throughout the observation period.

As we saw significant changes in the distribution of vacancies across occupations and districts, the matches might also have been affected by that. Exercise six (V6) sets the unconditional distribution of vacancies across occupations fixed on its 2013 level, i.e. assumes that no occupation has changed in importance over time. Exercise seven (V7) assumes that all there was no change in vacancies' regional unconditional distributions, i.e. the posting of vacancies has evolved the same way in each district. However, it is likely that the occupational composition varies between districts. In order to account for changes in the occupations in each district on their 2013 level. Related to this, occupations are likely not equally spread over the districts, but can be concentrated in particular regions. In order to account for regional changes by occupations separately, we set in exercise nine (V9) the conditional distribution of districts in each occupation on their 2013 level. Also here, it is not clear ex ante in which direction the number of overall matches would change, as the direction of the overall evolution of matches depends



Figure 11: Counterfactual Exercises on Vacancies

	2013-19	2013-21
Actual Decrease	.53	10.4
V0 Estimated Decrease	.31	10.56
V1 CF No Cellwise Mismatch	-1.61	5.39
V2 CF No change in cellwise mismatch	2.44	13.82
V3 CF Vacs Overall Constant, Dispersion Varying	1.68	8.01
V4 CF Vacs Cellwise Constant	2.44	9.18

Table 6: Counterfactuals Set 2

on the interaction between changes in vacancies' distribution and the estimated fixed effects of the different occupations and regions, respectively. Their equations are shown in Table 10 and a graphical overview is given in Figure 19. Table 11 reports the decrease in these scenarios until 2019 and 2021.

A comprehensive overview of all counterfactual exercises where vacancies are varied is in Table 12 in the appendix.

Counterfactual Vacations	Equation
V1 Tightness Constantly Equal to 1	$V_{odt}^1 = A_{odt}$
V2 No Change in Cell-Wise Tightness	$V_{odt}^2 = A_{odt} \cdot \frac{V_{od,2013}}{A_{od,2013}}$
V3 No Change in Overall Vacancies	$V_{odt}^3 = \beta_{o dt} \cdot \beta_{dt} \cdot V_{2013}$
V4 No Change in Cell-Wise Vacancies	$V_{odt}^4 = V_{od,2013} = \beta_{o d,2013} \cdot \beta_{d,2013} \cdot V_{2013}$

'acancies
'a

As Table 6 shows, the most pronounced differences to the observed matches are obtained in

the scenario (V1) of *No Mismatch*, and in the scenario (V2) of *No Change in Mismatch*. However, it is worth mentioning that scenario (V1) does not start on the same level in 2013 as the others. Exercise (V1) shows that about one half of the observed decrease in matches until 2021 can be explained by the mismatch between applicants in vacancies, as with same numbers of both within each region and districts, the overall decrease in matches would be only 5.39 percentage points (compared to the overall 10.4). In contrast, with no change in mismatch (V2), we would have an even stronger decline in matches of about 13.82 percentage points. Together with the observed increasing variation in tightness over time, we can conclude that there is a negative interaction between tightness and the district and occupational FE. If we consider 2019 as an endpoint, the results tend in the same direction, with even an increase in matches (1.61 pp.) in case of no mismatch and a decrease of 2.44 pp. in case of constant mismatch, compared to the overall decrease of 0.53 pp.

According to the observed decline in overall vacancies, we see that in scenario (V3) of constant vacancies overall we would obtain a decrease of 1.68 percentage points until 2019 and ob 8.01 percentage points until 2021. Thus, until 2021 about three quarters of the decline in matches stems from the change in vacancies, whereas before the Covid pandemic (2019), by changes in the number of applicants being more pronounced, the decrease of matches in this scenario would be more than three times as large than the observed decrease.

When holding disaggregated vacancies constant (V4), the decrease in matches is slightly stronger than in the previous scenario. This gives evidence that the observed change in the regional and occupational distribution of vacancies is rather beneficial for the number of matches, i.e. the shift is towards occupations and/or regions with higher FE.

Table 11 shows that in the additional counterfactual scenarios, matches would change relatively only slightly. There is some evidence that the observed switches in the occupational distribution of vacancies are rather towards occupations with better matching efficiencies, i.e. higher occupational FE, as in exercise V6 and V8 when holding vacancies' distribution across occupations constant, the decline in matches would be stronger than actually observed. Holding changes in the regional distribution of vacancies (V7 and V9) does not change the observed decline by much, pointing out to either relatively small changes in the regional distribution, or, towards regions with similar FE. Related to the concept of tightness, the fact that the distribution of applicants across regions and occupations might differ from the ones of vacancies, does not shrink matches down. In exercise V5 when assigning to vacancies the same distribution as to applicants, matches do also evolve very similarly. We have studied how the evolution of vacancies drive the number of overall matches. Next, we turn again to the supply-side. In order to include the three previously studied mechanisms - demographic change, change in educational choices and entry-rate into VET - into the matching function, we have to decompose the number of applicants in each district and occupation into the four educational groups. By the different entry rates into VET, it is obvious that the different sizes of the educational groups drive the built-up of applicants. Our augmented matching function including the shares of applicants with different groups shows that besides that, the matching itself is not affected significantly by education. The number of matches can thus be computed as

$$\hat{y}_{t} = \sum_{o} \sum_{d} \hat{M}_{odt} = \sum_{o} \sum_{d} \exp\left(\hat{c} + \hat{f}_{o} + \hat{f}_{t} + \hat{f}_{d}\right) \cdot V_{odt}^{\hat{\theta}_{1}} \cdot \left(A_{1odt} + A_{2odt} + A_{3odt} + A_{4odt}\right)^{\hat{\theta}_{2}}$$
(10)

with the estimation results from (8). Next, to include the mechanisms on the supply side, we denote the number of applicants by education, occupation and district by

$$A_{eodt} = i_{oedt} p_{edt} h_{edt} N_{dt}, \quad e = 1, 2, 3, 4.$$
 (11)

Note that (11) is chosen analogously to the first set of counterfactual exercises with one notable difference - we now include two separate terms which together describe the probability to be an applicant in a certain occupation given your education level:

- 1. The first factor i_{oedt} describes the share of VET applicants who apply for occupation o, given education and district.
- 2. The term p_{edt} describes the probability to apply for VET given the education and district.

Using this notation, we can distinguish between interest in VET and the decision for specific occupations. Unlike in the first set of counterfactual exercises, we are also able to disentangle the entry-rate into VET into the decision to apply and matching. Figure 12 shows the evolution of the interest in VET, i.e. the application rate for the different school degrees over time. The orange line represents the overall rate for Germany. In order to also report the variation across districts, the area between the first and the third quartile is greyed out. In line with our estimation results showing how education does slightly, but not significantly affect matching, we see an overall similar pattern to the VET-entry rates in Figure ??. The interest in VET is increasing among school leavers with a high school degree, and particularly in the last years decreasing for school leavers with a medium degree. Still on a very high level even exceeding one, also school leavers with a low degree tend to apply less often for VET. However, the rates greater than one also



Figure 12: VET Application Rate, by Degree

indicate than either many applicants with a low degree do either not find a match when leaving school directly, or they apply from a first apprenticeship into a new one. For the relatively small group of school leavers with no degree, we see a relatively stable application rate of about 15%.

In the next set of counterfactual exercises, we show how the different supply-side mechanisms affect the number of matches when accounting for regional and occupational disaggregation, application and matching separately. In the first exercise (A1), we assume that the number of school leavers stayed on their level from 2013 within each district. Our assumption is that this is the mechanism with the highest explanatory power and the counterfactual decrease of matches would be much less pronounced than the observed one. Second (A2), we assume no change in educational choices, i.e. no trend towards higher school degrees had been observed. The third exercise (A3) assumes a constant interest in VET over time, i.e. that application rates for each educational groups had not changed over time. In order to account for changes in the interest in specific occupations, we assume in exercise four (A4) that the shares of applicants applying for each occupations had been constant from 2013 onwards. As the decision for an occupation and

for VET are likely correlated, we additionally assume in the appendix in the fifth exercise (A34) that both the application rate and the occupational shares of applicants had been constant from 2013 onwards. Additionally, Table 15 and Figure 20 in the Appendix show the results of this counterfactual exercise.

Table 7 contains the equations for the applicants in this set of counterfactual exercises. A full comprehensive overview with the counterfactual equations is presented in Table 13 in the appendix.

A graphical overview over the exercises where only supply-side mechanisms vary is given in Figure 13. The first two columns in Table 8 show the resulting decline in matches until 2019 and 2021. We see that in the absence of the demographic change (A1), we would see only about half of the actual decrease in matches until 2021 (5 instead of 10 percentage points). The decline in interest in VET (A3), unlike often debated, can explain only 6% of the observed decline in matches until 2021. However, these results also show that in the recent years during the Covid pandemic, interest in VET has recovered again, as the decline in matches with no change in interest in VET would be even stronger than estimated until 2019 (2.62 versus 0.53). The observed change in occupational choices of applicants is slightly towards occupations with higher matching efficiencies, i.e. higher occupational FE, as exercise (A4) shows that without these change, the decrease in matches would be even stronger than the estimated one (1.21 pp). until 2019 and 11.8 pp. until 2021). Only little of the decrease is coming from changes in the educational choices of young adults, as they would results in almost similar number of matches than observed throughout the observation period. Table 15 in the appendix shows that there is some positive interaction between changes in the decision to apply for VET and the interest in different occupations. Taken together, we would observe a decline in matches of about 3percentage points until 2019 and, by the increasing application rate in the Covid pandemic, a decrease of 10.78 percentage points, similar in size to the observed decease.

Counterfactual	Equation
A1 No Demographic Change	$A_{odt}^{1} = \sum_{e=1}^{4} i_{eodt} p_{edt} h_{edt} N_{d,2013}$
A2 No Change in Educational Choices	$A_{odt}^{2} = \sum_{e=1}^{4} i_{eodt} p_{edt} h_{ed,2013} N_{dt}$
A3 No Change in Interest in VET	$A_{odt}^{3} = \sum_{e=1}^{4} i_{eodt} p_{ed,2013} h_{edt} N_{dt}$
A4 No Change in Occupational Choices	$A_{odt}^{4} = \sum_{e=1}^{4} i_{eod,2013} p_{edt} h_{edt} N_{dt}$

Table 7: Counterfactual Exercises on Supply-Side Mechanisms

As both the number of applicants and vacancies matter for matching, we next combine the two sets of counterfactual exercises. In order to account for changes in the number of vacancies, we choose the two most extreme ones: The case of no mismatch (V1) which would give a substantially higher number of matches in the end, and the case of no change in mismatch (V2) which would yield to an even stronger decline in matches than actually observed. Combining these two demand-side changes with the supply-side mechanisms, we obtain for each mechanisms on the supply-side a comparably higher and lower number of matches. Panels a) -d) of Figure 15 show the evolution of matches, by varying the supply-side mechanisms, in combination either with observed vacancies, vacancies in case of no mismatch and vacancies in case of no change in mismatch. Columns 3-6 of Table 8 show the resulting decline in matches until 2019 and 2021.



Figure 13: Counterfactuals Exercises on Supply-Side Mechanisms

	V0 Actual Vacs		V1 No Mismatch		V2 No Change Mismatch	
	13-19	13-21	13-19	13-21	13-19	13-21
A0 Actual Applicants	0.53	10.40	-1.61	5.39	2.44	13.82
A1 CF No Demographic Δ	-3.78	5.05	-5.96	-0.68	-1.42	8.66
A2 CF No Δ in Educ	0.44	10.73	-1.46	5.58	2.56	13.99
A3 CF No Δ in Interest	2.62	9.89	0.72	4.61	4.56	13.02
A4 CF No Δ in Occupations	1.21	11.8	-2.02	4.68	3.40	15.19

Table 8: Counterfactuals Set 3

The third and last reason why matches have been decreasing besides changes in the supplyand the demand-side are changes in the matching efficiency. The estimated year FE, as shown in Figure 10 in the matching equations proves that matching is getting worse over time, in particular during the Covid pandemic. Now, consider scenarios where the matching efficiency varies. First, in exercise (M.A0.V0) we assume that matching efficiency stayed constant on its 2013 level. We would assume the number of matches to be higher than actually observed due to the worsening matching over time. Next, we also combine the most important mechanism on the supply-side to matching in exercise (M.A1.V0), where we also assume no change in the number of school leavers from 2013 onwards.

By combining these two scenarios with the most important drivers on the demand-side, scenario (V1) of no mismatch between applicants and vacancies and (V2) of no change in mismatch, we obtain for each of the previous exercises a comparably higher number of matches (M.A0.V1 and M.A1.V1) and a lower one (M.A1.V2 and M.A1.V2). A comprehensive overview of the counterfactual equations is given in Table 14 in the Appendix. Figure 14 gives a graphical overview over those where vacancies are taken as observed. It can be seen that still the demographic change matters more than the worsening matching, but with both of them taken together, the decline of matches can be explained even better. Panel e(t) - f(t) in Figure 15 show the graphs with the evolution of matches in these counterfactual scenarios. Table 9 summarizes the obtained decrease of matches until 2019 and 2021. We can conclude that worsening matching explains about 19% of the observed decline in matching until 2021. There is a slightly positive interaction between demographic change and matching, as taking both of them together, we would have a decline of only about 3 percentage points until 2021 and could thus explain about 72% of the estimated decrease. When considering 2019 as an endpoint, the findings point in the same direction. Together with the observed slight decrease in matches, we would even observe an increase in matches in both of these scenarios.

	V0 Actual Vacs		V1 No Mismatch		V2 No change Mismatch	
	13-19	13-21	13-19	13-21	13-19	13-21
A0 Actual Applicants	0.53	10.40	-1.61	5.39	2.44	13.82
A1 CF No Demographic Δ	-3.78	5.05	-5.96	-0.68	-1.42	8.66
M.A0 CF No Δ in Matching	-0.12	8.59	-2.05	3.31	2.02	11.93
M.A1 CF No Δ in Matching	1 22	2.06	6 49	2.80	1.86	6 65
and Demogr.	-4.20	2.90	-0.42	-2.09	-1.00	0.00

Table 9: Counterfactuals Set 4



Figure 14: Counterfactual Exercises on Matching and Demographic Change

6 Conclusion

We study the recent evolution of the German VET market. This is an important labor market for young adults and characterized by a specific timing structure as well as local and occupational frictions. In recent years, the number of matches has been on a downward trend, with a particular drop in the number of matches during the time of the Covid pandemic. In this paper, we find multiple reasons for the decrease in matches: First, some mechanisms on the supply-side, especially demographic change, make the main target group applying for VET smaller. Second, we set up a matching function and study how its' different inputs - overall tightness, mismatch on the disaggregated level and matching efficiency - evolve over time. By estimating our matching function, we find that matching problems were growing during the Covid pandemic.



Figure 15: Counterfactuals Set 2 Mechanisms, Matching and Vacancies

Using a comprehensive set of counterfactual exercises, we study how the VET market would have evolved in the absence of changes in supply-side mechanisms or in the matching function over time. Our study provides an extensive analysis of a specific labor market and analyzes its matching structure in a detailed way. It can furthermore help policymakers to understand the different driving forces behind the current developments on the VET market. This can provide valuable insights, particularly in the view of the increasing shortage of skilled labor, which poses challenges for the economy and society.

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A Appendix



Figure 16: Demographic change and VET contracts by age



Figure 17: Occupational FE



Figure 18: Actual and estimated matches from equation 8

	2013-19	2013-21
Actual Decrease	.53	10.4
V0 Estimated Decrease	.31	10.56
V5 CF Same Distribution as Apps	0.02	10.21
V6 CF No change in uncond. occ. disp.	.78	11.36
V7 CF No change in uncond. reg. disp.	.27	10.52
V8 CF No change in cond. occ. disp.	1.11	11.73
V9 CF No change in cond. reg. disp.	.61	10.9

Table 11: Counterfactuals Set 2, Appended

Counterfactual Vacations	Equation
V5 Same Distribution of Apps and Vacs	$V_{odt}^5 = \alpha_{o odt} \alpha_{dt} V_t$
V6 No change in unconditional occupational distribution	$V_{odt}^6 = \beta_{d ot} \beta_{o,2013} V_t$
V7 No change in unconditional regional distribution	$V_{odt}^7 = \beta_{o dt} \beta_{d,2013} V_t$
V8 No change in conditional occupational distribution	$V_{odt}^8 = \beta_{o d,2013} \beta_{dt} V_t$
V9 No change in conditional regional distribution	$V_{odt}^9 = \beta_{d o,2013} \beta_{ot} V_t$

Table 10: Counterfactuals Vacancies (appended)

Counterfactual Matches	Equation
A0.V1: CF Tightness Constantly Equal to 1	$y_t^{A0.V1} = \sum_{o,d} E_{odt} \cdot A_{odt}^{\theta_1} \cdot A_{odt}^{\theta_2}$
A0.V2: CF No Change in Cell-Wise Tightness	$y_t^{A0.V2} = \sum_{o,d} E_{odt} \cdot \left(A_{odt} \cdot \frac{V_{od,2013}}{A_{od,2013}} \right)^{\theta_1} \cdot A_{odt}^{\theta_2}$
A0.V3: CF No Change in Overall Vacancies	$y_t^{A0.V3} = \sum_{od} E_{odt} \cdot \left(\beta_{o dt} \cdot \beta_{dt} \cdot V_{2013}\right)^{\theta_1} \cdot A_{odt}^{\theta_2}$
A0.V4: CF No Change in Cell-Wise Vacancies	$y_t^{A0.V4} = \sum_{o,d}^{0,a} E_{odt} \cdot V_{od,2013}^{\theta_1} \cdot A_{odt}^{\theta_2}$
A0.V5: CF Same Distribution of Apps and Vacs	$y_t^{A0.V5} = \sum_{\alpha d} E_{odt} \cdot \left(\alpha_{o odt} \alpha_{dt} V_t\right)^{\theta_1} \cdot A_{odt}^{\theta_2}$
A0.V6: CF No change in unconditional occu- pational distribution	$y_t^{A0.V6} = \sum_{o,d}^{o,a} E_{odt} \cdot \left(\beta_{d ot}\beta_{o,2013}V_t\right)^{\theta_1} \cdot A_{odt}^{\theta_2}$
A0.V7: CF No change in unconditional regional distribution	$y_t^{A0.V7} = \sum_{o,d} E_{odt} \cdot \left(\beta_{o dt}\beta_{d,2013}V_t\right)^{\theta_1} \cdot A_{odt}^{\theta_2}$
A0.V8: CF No change in conditional occupa- tional distribution	$y_t^{A0.V8} = \sum_{o,d} E_{odt} \cdot \left(\beta_{o d,2013}\beta_{dt}V_t\right)^{\theta_1} \cdot A_{odt}^{\theta_2}$
A0.V9: CF No change in conditional regional distribution	$y_t^{A0.V9} = \sum_{o,d} E_{odt} \cdot \left(\beta_{d o,2013}\beta_{ot}V_t\right)^{\theta_1} \cdot A_{odt}^{\theta_2}$

 $Table \ 12:$ Counterfactual Exercises with varying Vacancies

Counterfactual Matches	Equation
Counterfactuals where only supply-side mechanisms change	
A1.V0: CF No Demographic Change	$y_{t}^{A1.V0} = \sum_{o,d} E_{odt} \cdot V_{odt}^{\theta_{1}} \cdot \left(\sum_{e=1}^{4} i_{eodt} p_{edt} h_{edt} N_{d,2013}\right)_{o}^{\theta_{2}}$
A2.V0: CF No Change in Educational Choices	$y_{t}^{A2.V0} = \sum_{o,d} E_{odt} \cdot V_{odt}^{\theta_{1}} \cdot \left(\sum_{e=1}^{4} i_{eodt} p_{edt} h_{ed,2013} N_{dt}\right)^{\theta_{2}}$
A3.V0: CF No Change in Interest in VET	$y_{t}^{A3.V0} = \sum_{o,d} E_{odt} \cdot V_{odt}^{\theta_{1}} \cdot \left(\sum_{e=1}^{4} i_{eodt} p_{ed,2013} h_{edt} N_{dt}\right)^{\theta_{2}}$
A4.V0: CF No Change in Occupational Choices	$y_t^{A4.V0} = \sum_{o,d} E_{odt} \cdot V_{odt}^{\theta_1} \cdot \left(\sum_{e=1}^4 i_{eod,2013} p_{edt} h_{edt} N_{dt}\right)^{\theta_2}$
A34.V0: CF No Change in Interest in VET and Occupations	$y_t^{A34.V0} = \sum_{o,d} E_{odt} \cdot V_{odt}^{\theta_1} \cdot \left(\sum_{e=1}^4 i_{eod,2013} p_{ed,2013} h_{edt} N_{dt}\right)^{\circ_2}$
Counterfactual where vacancies and supply-side mechanisms cha	nge
A1.V1: No Demographic Change, Tightness Constantly Equal to 1	$y_t^{A1.V1} = \sum_{o,d} E_{odt} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{edt} h_{edt} N_{d,2013}\right)^{\theta_1 + \theta_2}$
A2.V1: No Change in Educational Choices, Tightness Constantly Equal to 1	$y_t^{A2.V1} = \sum_{o,d} E_{odt} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{edt} h_{ed,2013} N_{dt}\right)^{\theta_1 + \theta_2}$
A3.V1: No Change in Interest in VET, Tightness Constantly Equal to 1	$y_t^{A3.V1} = \sum_{o,d} E_{odt} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{ed,2013} h_{edt} N_{dt}\right)^{\theta_1 + \theta_2}$
A4.V1: No Change in Occupational Choices, Tightness Constantly Equal to 1	$y_t^{A4.V0} = \sum_{o,d} E_{odt} \cdot \left(\sum_{e=1}^4 i_{eod,2013} p_{edt} h_{edt} N_{dt}\right)^{\theta_1 + \theta_2}$
A1.V2: No Demographic change, No Change in Tightness	$y_t^{A1.V2} = \sum_{o,d} E_{odt} \cdot \left(A_{odt} \cdot \frac{V_{od,2013}}{A_{od,2013}} \right)^{\theta_1} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{edt} h_{edt} N_{d,2013} \right)^{\theta_2}$
A2.V2: No Change in Educational Choices, No Change in Tightness	$y_t^{A2.V2} = \sum_{o,d} E_{odt} \cdot \left(A_{odt} \cdot \frac{V_{od,2013}}{A_{od,2013}} \right)^{\theta_1} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{edt} h_{ed,2013} N_{dt} \right)^{\theta_2}$
A3.V2: No Change in Interest in VET, No Change in Tightness	$y_t^{A3.V2} = \sum_{o,d} E_{odt} \cdot \left(A_{odt} \cdot \frac{V_{od,2013}}{A_{od,2013}} \right)^{\theta_1} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{ed,2013} h_{edt} N_{dt} \right)^{\theta_2}$
A4.V2: No Change in Occupational Choices, No Change in Tightness	$y_t^{A4.V2} = \sum_{o,d} E_{odt} \cdot \left(A_{odt} \cdot \frac{V_{od,2013}}{A_{od,2013}}\right)^{\theta_1} \cdot \left(\sum_{e=1}^4 i_{eod,2013} p_{edt} h_{edt} N_{dt}\right)^{\theta_2}$

 $Table \ 13:$ Counterfactual Exercises with varying Vacancies and Supply-Side Mechanisms

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Counterfactual Matches	Equation
M.A0.V0: No Change in Matching Efficiency	$y_t^{M.A0.V0} = \sum E_{od,2013} \cdot V_{odt}^{\theta_1} \cdot A_{odt}^{\theta_2}$
${\sf M}.{\sf A0}.{\sf V1}:$ No Change in Matching Efficiency, Tightness Constantly Equal to 1	$y_t^{M.A0.V1} = \sum_{o,d}^{o,d} E_{od,2013} \cdot A_{odt}^{\theta_1 + \theta_2}$
M.A0.V2: No Change in Matching Efficiency, No Change in Tightness	$y_t^{M.A0.V2} = \sum_{o,d} E_{od,2013} \cdot \left(A_{odt} \cdot \frac{V_{od,2013}}{A_{od,2013}} \right)^{\theta_1} \cdot A_{odt}^{\theta_2}$
M.A1.V0: No Change in Matching Efficiency and Demogr.	$y_t^{M.A1.V0} = \sum_{o,d} E_{od,2013} \cdot V_{odt}^{\theta_1} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{edt} h_{edt} N_{d,2013}\right)^{\theta_2}$
M.A1.V1: No Change in Matching Efficiency and Demogr., Tightness Constantly Equal to 1	$y_t^{M.A1.V1} = \sum_{o,d} E_{od,2013} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{edt} h_{edt} N_{d,2013}\right)^{\theta_1 + \theta_2}$
M.A1.V2: No Change in Matching Efficiency and Demogr., No Change in Tightness	$y_t^{M.A1.V2} = \sum_{o,d} E_{od,2013} \cdot \left(A_{odt} \cdot \frac{V_{od,2013}}{A_{od,2013}}\right)^{\theta_1} \cdot \left(\sum_{e=1}^4 i_{eodt} p_{edt} h_{edt} N_{d,2013}\right)^{\theta_2}$

 $Table \ 14: \ \mbox{Counterfactual Exercises with varying Vacancies, Supply-Side Mechanisms and Matching}$

	V0 Actual Vacs	
	13-19	13-21
A0 Actual Applicants	0.53	10.40
A3 CF No Δ in Interest	2.62	9.89
A4 CF No Δ in Occupations	1.21	11.8
A34 CF No Δ in Interest and Occupations	3.25	10.83

Table 15: Counterfactuals Appendix



Figure 20: Counterfactual Exercises on Supply-Side Mechanisms (appended)



Figure 19: Counterfactual Exercises on Vacancies (appended)



Figure 21: Changes in conditional distributions to previous year each